ABSTRACT

Title of thesis: EXAMINING THE EFFECT OF RETAIL MARIJUANA OUTLETS ON CRIME IN THEIR LOCATLITIES AND THEIR NEIGHBORING AREAS

Alex Liu, Master of Arts, 2019

Thesis directed by: Professor Peter Reuter
Department of Criminology and Criminal Justice
School of Public Policy

With the growing legalization of marijuana across the United States, there is also increasing concern with the effect that marijuana dispensaries may have on the communities they are established in. This study focuses on the effects that these dispensaries may have on crime, not only in the immediate communities they are located in, but also the surrounding communities. Drawing from arguments from crime pattern theory, locations have certain characteristics that can promote or discourage crime from occurring in and around those locations. In order to test this, geospatial econometric methods that have not been fully explored in the field of criminology are used to test this relationship. Using data collected from the State of Washington and City of Tacoma, this study finds several interesting effects of marijuana dispensaries on crime rates, and lists several implications and future directions for both researchers and policymakers.

EXAMINING THE EFFECT OF RETAIL MARIJUANA OUTLETS ON CRIME IN THEIR LOCALITIES AND THEIR NEIGHBORING AREAS

by

Alex Liu

Thesis submitted to the Faculty of the Graduate School
of the University of Maryland; College Park in partial
fulfillment of the requirements for the degree of Master
of Arts 2019

Advisory Committee:
Professor Peter Reuter, Chair
Assistant Professor Lauren Porter
Assistant Professor Greg Midgette

Table of Contents

List of Tables

List of Figures

1. Introduction:

1.1. Introduction

The landscape surrounding marijuana in the United States is undergoing significant changes, especially with regards to its regulation and legal status. With these legal changes, the public attitudes and perceptions towards marijuana and its legalization have become more favorable. Now, the majority of people are in favor of the allowance of marijuana for medical purposes with 73% in favor of it as of March 2010, (Pew Research Center, 2010) as well as its overall legalization with 61% in favor as of 2018, the highest it has ever been (General Social Surveys, 2018). This is compared to just a couple years ago, with only 17% in favor in 1991 and 32% in favor in 2002 (Pew Research Center, 2013). And so with the changing attitudes towards marijuana becoming more positive, an increasing number of states are decriminalizing, allowing medical use, and legalizing recreational marijuana. Therefore there is an equally increasing interest in the effects of marijuana, not just from its use, but also through the dispensaries in which they are sold; accompanying the establishment of these dispensaries are the concerns that they potentially have on public health outcomes and crime in the neighborhoods and communities they are located in.

There has been some controversy and pushback against the establishment of marijuana dispensaries due to assumptions that dispensaries would increase crime and pose other problems in the areas where they are located (California Police Chief's Association, 2009; McDonald & Pelisek 2009). And this assumption is not unreasonable: since the legalization of marijuana in several states, there have been multiple reports of dispensaries being victimized by burglaries and robberies (Dokoupil & Briggs, 2014;

McCarty, 2018; Sun, 2018; KOMO, 2014; Winston, 2016). Not only does it pose problems for the dispensaries themselves, but also raises concerns for the neighborhoods around them. This idea that marijuana dispensaries are related to increased crime has been highly influential with policymakers; it has resulted in measures being taken by localities to ban or heavily regulate marijuana dispensaries (Ferguson, 2014; Zheng, 2014). In Washington State, there even have been talks of increasing the punishment for robberies against marijuana dispensaries to combat this issue (Wasserman, 2018).

Yet the literature establishing this relationship between marijuana dispensaries is mixed and limited. Work by Morris et al. (2014) found no relationship between medical marijuana laws and crime rates through state difference-in-difference estimates. Similar results were found in a study conducted by Maier et al. (2017) looking at differences in crime rates between states based on their legalization status. These inconclusive results would seem to make sense, due to the fact that there is variation both between and within states in how they implement their laws and regulations towards marijuana. With differential definitions and policies for each state, the marijuana markets would not be the same from one state to another, and this heterogeneity does not lend well for such comparisons (Pacula & Smart, 2017). The different ways in which states define their laws makes comparisons difficult between them, and even within states there is large variation in how localities regulate marijuana which introduces additional complications (National Alliance for Model State Drug Laws [NAMSDL], 2016).

This thesis will examine the spatial patterns of crime in the city of Tacoma, Washington in relation to the locations of marijuana dispensaries throughout the city. This thesis adopts methodological strategies from spatial econometrics that have not been fully applied in criminology in an attempt to provide a more detailed look into the patterns of crime through a geospatial lens. In order to do so, crime pattern theory is being used to establish the theoretical background; crime pattern theory integrates concepts from routine activity theory and the geometric theory of crime into an overarching environmental theory of crime. This perspective allows for the interaction between offenders and their environments, and takes into account the criminogeneity of certain locations and facilities as crime attractors and crime generators. As such, this study will use crime pattern theory and spatial methods to develop models to examine the effects that marijuana dispensary facilities, the socio-economic characteristics, and the socio-demographic characteristics of the city have on property crime and violent crime.

1.2. History and Legal Status of Marijuana in the United States

Marijuana has been used in the United States since the early 17th Century to produce hemp products; formed from different parts of the cannabis plant, hemp was used for many essential products such as oil, wax, fuel, rope, and fibers/clothing. After the Mexican Revolution of 1910, there was a large influx of Mexican immigrants to the United States, and with them came the introduction of the recreational use of marijuana into American culture. And so, the Marijuana Tax Act of 1937, prohibited the use, sale, and possession of cannabis unless for certain authorized medical and industrial uses, which effectively criminalized marijuana. So, marijuana was legal in the United States up until this point, although many states had outlawed marijuana before this (Wang & Herrera, 2014; Frontline, 2018). The Controlled Substances Act, under the Comprehensive Drug Abuse Prevention and Control Act of 1970, strengthened the prohibition of marijuana even further; it was passed to regulate certain substances under five different schedules, or classifications. The highest and most restrictive classification, Schedule I, defines drugs that have no medical use with a high potential for abuse and physical/psychological dependence. Marijuana and its cannabinoids are currently listed under this classification as Schedule I drugs (Anderson et al., 2013; Drug Enforcement Agency [DEA], 2018; Hansen et al., 2018).

However, the attitudes and political climate towards marijuana has shifted in the past several decades since its classification as a Schedule I drug; attitudes have begun to swing in the other direction and in favor of its medical use and legalization. Starting in 1973, Oregon became the first state to decriminalize marijuana possession. And in 1996 through Proposition 215, otherwise known as the Compassionate Use Act, California became the first state to legalize medical marijuana at the state level; Oregon and Washington followed suit soon after in 1998 (Anderson et al., 2013; Frontline, 2018). In 2012, Colorado, through Amendment 64, and Washington, through Initiative 502, became the first two states to legalize the recreational use of marijuana. To this day, 33 states, the District of Columbia, Guam, and Puerto Rico have medical marijuana programs. 10 of these states, plus the District of Columbia, also have legal recreational marijuana programs (NAMSDL, 2016; National Conference of State Legislatures [NCSL], 2018).

On August 29, 2013, the Cole Memorandum was issued, which stated that the Department of Justice would not prosecute and enforce federal marijuana prohibition in states that legalized and effectively regulated it. It represented a shift from federal control to state and local jurisdictions control over marijuana in the US (Cole, 2013). In May 2014, the Rohrabacher – Farr amendment passed, which had similar intentions to the

Cole Memorandum, prevented the Department of Justice from interfering with state implementation of marijuana laws (H.R. 2578, 2016). These two pieces of legislation helped to protect the states that had already legalized marijuana and propel the implementation of medical marijuana among more states. However, the Cole Memorandum was recently rescinded under the new administration on January 4, 2018, with the impacts of the rescission yet to be seen. Just a year later on January 9, 2019 a new bill, H.R. 420, was introduced by Representative Earl Blumenauer in order to regulate and decriminalize marijuana at the federal level. This bill would aim to regulate marijuana similarly to alcohol. This provides an interesting development for the political atmosphere around marijuana and for its future legal status in the United States (H.R. 420, 2019).

2. Literature Review:

2.1. Theoretical Framework

2.1.1. Environmental Criminology

Environmental criminology is composed of a group of theories that focus on criminal events and the circumstances in which they are committed; instead of the focus being on the offender as with more traditional criminological theories, the environmental perspective is interested in crime itself and the dynamics of crime. Additionally influenced by psychology, geography, and political science, the environmental perspective is built upon the foundations of other disciplines. It seeks to explain crime patterns through environmental influences, derived from sociodemographic, temporal, and spatial characteristics. Environmental criminology is based upon three premises: (1) criminal behavior is heavily dependent on the immediate environment in which it occurs

(2) that the distribution of crime across time and space is non-random and (3) that the role of criminogenic environments and crime patterns are invaluable in the investigation, control, and prevention of crime (Wortley & Mazerolle, 2008; Wortley & Townsley, 2016).

The environmental perspective can be approached through three levels of analysis: the macro-level, meso-level, and the micro-level (Wortley & Mazerolle, 2008; Wortley & Townsley, 2016). The macro-level examines crime patterns at a highly-aggregated level: between countries, between states/counties within a particular country, or between cities within a state. This sort of analysis can be traced back to Andre-Michel Guerry and Adolphe Quetelet, who were among the first to analyze and map crimes. From their findings and crime maps in France, they found that crimes were not evenly distributed across the country, and that violent crimes were higher in poorer areas while property crimes were higher in wealthier areas (Anselin et al., 2000). From this they suggested that property crimes stemmed from opportunity. And the role that opportunity plays in crime events has become a key element in the environmental perspective; so, the use of maps to depict crime trends has become essential in the analysis of crime.

The meso-level approach delves into a lower aggregation level and unit of analysis, and looks at crime through the subareas of a city. From this, there are several levels of aggregation that can be examined here, from areas such as neighborhoods and suburbs or street segments (Wortley & Mazerolle, 2008; Wortley & Townsley, 2016). A major contribution to this approach comes from sociology and from the human ecology movement by the Chicago School. They applied the premise of ecology, to study the individual components as part of a whole, to human behavior and crime; so the human ecology approach focused on the spatial relationships between people and their environment. Along this line of thinking, the city was conceptualized as an organism made up of many components and sub-communities which have influences on one another. And within those sub-communities are people who have relationships with one another and influence one another. These relationships and influences between people is also applicable to their environments and communities. (Park & Burgess, 1925).

Lastly, the micro-level analyzes the crime site itself, such as building characteristics, location, its immediate surroundings, and security measures. This level focuses on the small individual elements that comprise of the environment that influence decision making and behavior. So, the psychology on the causes of behavior and decision making can be noted; there are individual traits and dimensions that drive behavior and contribute to differences from person to person. Many traditional criminological theories look at offenders and these individual differences to explain criminal behavior. But these decisions and behaviors are subject to outside influence, and one's actions can shift along with the situational contexts. So these circumstances that crimes are committed in are additionally crucial for understanding criminal behavior (Wortley & Mazerolle, 2008; Wortley & Townsley, 2016). This concept of understanding situational contexts is highlighted in ""crime prevention through environmental design", or CPTED, by C. Ray Jeffery's work in 1971 and the concepts of "defensible space" by Oscar Wood (1972) and situational crime prevention by Ronald Clarke (1992); all three emphasize the physical characteristics of a location and the opportunity structures that make a location prone to crime (Cozens & Love, 2015; Clarke, 2009; Schneider, 2005).

This project will primarily be focused at the meso-level analysis, looking at neighborhoods and how they may affect one another. The unit of analysis is at the census block group level, which is how neighborhoods are being conceptualized for the basis of this study. However, some aspects at the micro-level will be examined and taken into account, such as the location characteristics of dispensaries as well as the elements of the immediate surroundings. These factors are included in order to take into account for heterogeneity between dispensaries and what goes on right around them, rather than looking at the larger neighborhood as a collective.

2.1.2. Social Disorganization Theory

At the meso-level, social disorganization theory examines the socioeconomic and demographic characteristics of neighborhoods and how they are related to crime rates. Shaw and McKay (1942) build upon the work conducted by Park and Burgess (1925) on human ecology, and were interested in looking at patterns of juvenile delinquency within cities. They believed that illegal activity was somehow related to their environment, and found that these rates of juvenile delinquency were related to spatial patterns in the city (Bernard, Snipes, & Gerould, 2015). These patterns were relatively stable within these areas, even as over time the composition of the population living in those areas changed. Shaw and McKay (1942) found that the differentiating characteristics of these neighborhoods were due to physical status, low economic status, and population instability, and that these attributes were associated with rates of delinquency. They concluded that these attributes stemmed from the changing growth patterns of new residents moving in and out of these transitional areas, thus resulting in crime, delinquency, and other social problems; heterogeneity of the population contributed to cultural instability and weakened social controls through the disruption of social institutions, values, and norms (Bernard et al., 2015).

Weakened social controls can also manifest apart from this ethnic and population heterogeneity. Differential value systems in these communities can also be reflective of their socioeconomic status; areas of lower economic status have wide varieties of social norms and behaviors, ranging from conventional and prosocial to delinquent and criminogenic. These conflicting norms and standards operate in tandem with one another, and what may be considered right and accepted to some groups in the community is seen as wrong and improper for others. Thus, individuals are presented with two different opportunities and competing systems: they can subscribe to conventional and socially acceptable methods to achieve this, or through delinquent or criminal avenues (Shaw & McKay, 1942). This represents an organizational base in the community that is weak and unable to exert sufficient formal and informal social control on local youth (Sampson & Groves, 1989). This is contrast to communities of higher economic status that are generally characterized by the universality of conventional norms and values. These areas are consistent in their accepted values and norms, so there is more social control in being able to protect these values while discouraging those that are in opposition (Shaw & McKay, 1942).

2.1.3. Routine Activity Theory

Narrowing the scope to the micro-level of the environmental criminology perspective, routine activity theory provides a framework which could explain why crime rates may be affected by the addition of recreational marijuana dispensaries in certain areas. Routine activities are referred to as any of the daily, weekly, etc. activities we undertake during the course of our lives; school, work, recreation, and entertainment can all be considered as part of these routine activities. These are legal activities, and are generally undertaken by everyone and are commonplace. Under routine activity, crime and illegal activities are therefore dependent on other activities, so then the spatial and temporal construction of these legal routine activities should have an impact on crime in a given area. So, these activities and factors in addition to the following three elements conjunction may be of consideration for explaining crime rates.

According to routine activity theory, there are three main components for a crime to occur: (1) the presence of a motivated offender; (2) a suitable target, which can be defined by value, visibility, accessibility, and inertia; an (3) the lack of capable guardians against crime, which can be persons such law enforcement or place managers or inanimate security measures such as cameras. The presence of all three conditions provides the most opportunity and likelihood for a crime to occur. The lack of any one of these conditions is sufficient enough to prevent a crime from happening (Clarke & Felson, 1993; Cohen & Felson, 1979; Eck & Weisburd, 1995). Routine activity theory allows for both a macro and micro perspective when explaining crime. The macro level approach examines the social characteristics and structure of society that allows for the offenders, targets, and guardians to intersect. The micro level perspective examines this interaction between these three components. A majority of the emphasis has been on this micro-level perspective, and variation in these three components at a location level can be indicative of whether it would be prone or resistant to crime. Similar to suggestions by CPTED mentioned earlier, enhanced security features based on these three components can act as “target hardening” to make it more difficult to victimize.

2.1.4. Geometric Theory of Crime

Pulling ideas from both social disorganization theory and routine activity theory, the geometric theory of crime, as developed by Brantingham and Brantingham (1981), specifically examines the geography of criminal events. It seeks to explain crime patterns based on the distributions of human activities through a spatial and dimension, and how those activities create perceived opportunities of crime. Within this theory, the environment is conceptualized through the environmental backcloth; it is constructed from the physical environment, social and cultural norms, legal dimensions, and other institutions. This backcloth is dynamic, and is representative of the ever-changing environment, as it can be influenced by someone once they enter it and influences their actions as well.

The geometric theory of crime also focuses on the idea of nodes paths, and edges to show where crimes occur within activity and awareness spaces (Andresen, 2010). Activity spaces are formed through a person's routine activities and are made up of the nodes and paths that they frequent. Their awareness spaces develop from these frequented locations, and consist of the knowledge they gain from habitually going to these places. Nodes are places that people travel to and from, and which most time is spent: home, work, school, businesses, and recreational and entertainment sites. Therefore, these are the areas in most crime is concentrated, due to the amount of time being spent in these locations. Paths are the ways to travel between these nodes, such as roads, highways, and sidewalks. These paths can also be areas in which crime concentrates, especially major roads and areas where there is a large amount of traffic. Edges are the perceptual boundaries between areas where people are conducting their activities, such as boundaries of neighborhoods or different districts within a city. These edges can be distinct and physical or be subtle changes from one area to the next. Edges are areas where the physical structure and features alongside the idea that outsiders and strangers can be more unnoticed or accepted create criminal opportunities (Brantingham & Brantingham, 1993a; Brantingham & Brantingham, 1993b; Brantingham & Brantingham, 1995).

Crimes occur in these areas as a result of potential offenders having similar activity and awareness spaces and patterns as potential victims. Offenders, just as the rest of the population, have daily patterns of behaviors and activity spaces; as they become more familiar with these areas and develop awareness spaces, they recognize more opportunities for crime. Most offenders will commit crimes in areas in which they are familiar with, and so these shared activity and awareness spaces between offenders and victims therefore become the opportunity spaces for which crimes can occur; it is this intersection that leads to criminal events (LaRue, 2013). Thus, the geometric theory of crime would expect to see that the majority of crimes would be committed in a small percentage of an available area, concentrated around these nodes that offenders and the rest of the population frequent.

2.1.5. Crime Pattern Theory

Crime pattern theory is the culmination of and builds off of the basic frameworks of the previously mentioned theories; as an overarching environmental criminological theory, Brantingham and Brantingham (1993) took their geometric theory of crime and developed it further using concepts social disorganization theory and routine activity theory. It takes ecological and environmental characteristics to explain the causes of crime. It suggests that crimes don't occur randomly or uniformly across time and space. They are highly patterned and often localized in areas: where not all areas experience crime and not all people commit crimes; these patterns are influenced by daily behaviors and an individual's routine activity spaces and awareness spaces. These reflect activity nodes, pathways, and edge effects for the individual. Criminal events are also the result of the environmental backcloth and the site/situation. The unifying feature of crime pattern theory that brings together the other theories is the crime template (Andresen, 2010). This crime template is a result of environmental cues being interpreted by potential offenders to find targets of crime; it is learned by these offenders whether these cues dictate if a target of crime is suitable or not (Eck & Weisburd, 1995). Thus, this learned behavior becomes this template that is used for victim and crime site selection. Crime templates are relatively stable and influence future behavior; but multiple crime templates can be created, each to a certain crime or particular location (Andresen, 2010).

Crime pattern theory identifies crime generators and crime attractors when dealing with the criminogeneity of locations and characteristics of places. It suggests that crime occurs and is patterned through the pulls and pushes of activities across locations in the urban environment; locations and facilities influence their surrounding environments, and some have more crime clustered around them. There are four types of locations: crime generators, crime attractors, crime-neutral areas, and crime detractors (Brantingham & Brantingham, 1995). Crime generators are not inherently criminogenic locations; they pull large amounts of people towards them, which in turn bring together offenders and targets. These are for reasons unrelated to any particular criminal motivation or subsequent crime they would commit. Thus, most crimes committed near these crime generators are opportunistic and spontaneous. On the other hand, crime attractors have certain characteristics, generally criminal opportunities, which pull people in. These existing criminal opportunities are acknowledged and known, thus pulling in individuals whom would take advantage of them, and are generally motivated offenders and repeat offenders. Crime-neutral areas neither attract motivated offenders nor create criminal opportunities; crimes are instead committed occasionally by local insiders to that area. Crime detractors are locations that would push people away, and therefore push crime away as well; with less people interacting, there is a decreased likelihood for potential offenders and victims to come into contact with one another. The difference here between the generators and attractors is that crimes result from crime generators through the bringing together of large amounts of people, resulting in offenders and targets coming together; crime attractors have known criminal opportunities that pull offenders to commit crimes in that area. However, locations are unlikely to only be categorized as purely one of these mentioned categories, and are more often than not a mix (Kinney et al. 2008).

2.1.6. Marijuana and Crime in Tacoma

Of the previously outlined theories, crime pattern theory and routine activity theory are the two that are of the most interest for examining the effect of marijuana dispensaries on crime rates in Tacoma. Specifically for crime pattern theory, the concept of crime attractors and generators is the main explanatory mechanism for how dispensaries affect crime rates. In routine activity theory, crime rates are affected by the presence of security measures and capable guardians at the dispensary. Despite originating from separate theories, attributes of routine activity may influence whether the dispensary is a crime attractor/generator and vice versa. So, these mechanisms taken together and their interactions would determine whether marijuana outlets would increase or decrease crime.

Applying crime generators and attractors of crime pattern theory to recreational marijuana dispensaries, dispensaries would be a mix of both generators and attractors. In the current climate regarding marijuana and legalization, dispensaries can act as a crime generator due to “marijuana tourism”; this is when individuals travel from another area where marijuana is not legal or available to the specified area to buy/use marijuana where it is legal and available. This would bring a larger number of people to a dispensary and to an area, subsequently increasing the likelihood for offenders and targets to meet. Additionally, dispensaries located in commercially zoned areas or commercial land-use areas in comparison to areas such as residential and civic-institutional-recreational areas would naturally have more traffic flow through them as other businesses are also pulling in more people to the area; but dispensaries would also be pulling in additional customers due to its nature of being a business as well. Marijuana dispensaries also act as crime attractors in that they pull in offenders similarly to how they are targets in routine activity theory as mentioned earlier; customers are entering with cash and leaving with marijuana, which makes them prime targets. The dispensaries themselves can be targets as well, depending on the level of security they have, as they also deal primarily with cash transactions and have stocks of marijuana. These factors can attract motivated offenders to commit crimes and present criminal opportunities at or near the dispensary.

Moving on to routine activity theory, it suggests that dispensaries have unique characteristics that contribute to an increase of crimes in an area. Being a predominately cash-based business with stocks of marijuana, it makes dispensaries a suitable target for offenders to obtain these goods; since marijuana is still illegal federally, many banks and credit institutions refuse to do business with marijuana dispensaries. So, they must deal only in cash due to not being able to accept credit or debit cards. In addition, guns are not allowed within dispensaries because it would be considered trafficking according to the Controlled Substances Act, which means less security for those working there (Winston, 2016; Wasserman, 2018). Thus, dispensaries can be at risk for crimes such as burglaries and robberies due to the presence of cash and marijuana with limited security. The employees can be at risk for violent crimes they are working there and are responsible for securing the marijuana and cash on the premises. In addition, the clients are at risk for violent crimes like robbery as well, as they are going to the dispensary with cash and leaving with marijuana products. Since the preexisting medical and newer recreational marijuana systems were integrated in Washington after recreational marijuana was implemented under Initiative 502 (I-502), medical marijuana patients therefore have to go to recreational dispensaries to get their medical marijuana. These patients are generally of the older population and are sick or have chronic illnesses, and are thus vulnerable and prime targets of crime as well.

Conversely, dispensaries can also decrease the number of crimes in an area according to routine activity theory. Dispensaries may employ several types of security features in order to make their location "hardened" against crime and reduce being targets of crime. Security guards can be hired to provide protection, and security cameras can be installed as well to act as capable guardians to reduce the dispensaries' and/or customers' suitability as a target and likelihood of being victimized. This can decrease crime in the immediate vicinity around the dispensary and possibly displace crimes to other neighboring areas (Freisthler et al., 2013). So it is possible for dispensaries to actually reduce crime, but it is under the stipulation that they have sufficient security measures to deter motivated offenders. Under crime pattern theory, it is also possible that dispensaries can act as crime detractors through the displacement of illicit drug markets. With the implementation of a dispensary that provides legal marijuana, the illicit market for marijuana may be displaced and pushed into neighboring areas; crimes associated with the illicit drug market and sales of drugs would decrease in those areas. This theory is supported by work done by Brinkman (2017) and suggests an alternative mechanism in how dispensaries may have protective effects.

Thus, there are several potential mechanisms at play here that may influence crime rates at the neighborhood level. At the meso-level of analysis, marijuana outlets in a neighborhood can act as crime generators or attractors. They may pull large amount of people over the course of their business operations and thus provide opportunities for offenders and victims to interact and crime to result. At the same time, the properties of marijuana outlets can make them attractive to criminals, and so they may flock to dispensaries in hopes of successfully committing crimes. At the more micro-level, the characteristics of the individual dispensary may affect crime occurring immediately in its vicinity and the resultant neighborhood as a whole. At the same time, they may act as crime detractors in pushing people out of an area. This can be seen if dispensaries would displace illicit drug markets, specifically marijuana, due to the presence of legal marijuana. Pushing these individuals from the areas in which dispensaries are located could displace crimes related to illicit drug markets into other areas. Taking concepts from routine activity theory, a dispensary can increase or decrease crime dependent on how they regulate capable guardians. Dispensaries can be more prone to crimes and crimes in an area may go up if they lack security measures to protect their stocks of marijuana and cash on site. On the other hand, with sufficient measures of security dispensaries may protect themselves and deter crimes from occurring. Security cameras, security guards, barred windows, reinforced doors, and other security measures can deter crimes not only against the dispensary, but also other places in the vicinity.

Not only do these effects exist at the neighborhood level, but the implementation of recreational marijuana would impact the city of Tacoma as a whole as well. The aggregate crime rates in Tacoma can be affected by the addition of marijuana outlets through several mechanisms: as mentioned previously, the availability of marijuana may have effects on alcohol consumption and for other drugs as well. Having marijuana outlets would mean that there is more marijuana available in the city, and therefore it would not be unfair to assume that these complimentary and substitution effects at the local level would also extend to the aggregate city level. And in line with crime pattern theory, the availability of marijuana and recreational outlets in Tacoma can make the city as a whole a crime generator and attractor; drug tourism can occur where people are drawn to Tacoma in order to access legal marijuana. Since local municipalities can choose whether or not to allow dispensaries, there are other cities near Tacoma that do not allow dispensaries within their city limits. And so people from neighboring municipalities that do not have access to legal marijuana can travel to Tacoma to buy marijuana. This could affect crime rates in Tacoma as a whole, similarly to how they may affect crime rates at the more local neighborhood level within Tacoma.

2.2. Existing Literature

Exploring the environmental and geographical characteristics within an area poses a unique challenge with regards to spatial patterns of criminal behavior. There are differential effects as a result of physical and social features of the area: physical features such as businesses, land uses, and the structural layout of a neighborhood produce varying outcomes within themselves, and compared to social features such as the sociodemographic and economic backgrounds of the residents there is even more variation. There are also reciprocal influences between a location and what goes on at that place. Peoples' environments mold their decision making and actions, and their actions can also alter their surroundings. In addition, definitional issues are abound for important determinants in environmental criminology. Questions exist on how to differentiate between neighborhoods and their boundaries, the right size for a buffer zone, what unit of analysis to look at, what statistical and spatial models to use, and so on; thus, depending on the question of interest, many variations of methods and techniques can be employed to examine individuals, their environments, and crime. The following studies provide several perspectives with their methodologies on how to address various elements when investigating environmental characteristics of crime.

2.2.1. Marijuana Legalization and Crime

Before examining the impact of marijuana dispensaries in states that have legalized it for medical and/or recreational purposes, it must first be determined if there is any difference between the states that have legalized marijuana and those that have not. Wang & Herrera (2014) briefly explore the history of marijuana and marijuana regulation within the United States. The authors focus on the state of Colorado, and examine arrest rates dating back to 1995. This is to examine changes in arrest rates since the introduction of medical marijuana due to its establishment of medical marijuana in 1996. Using basic descriptive statistics, they look at changes in trends and find that the average arrest rates are lower for total, violent, and drug-related arrests after 2000 compared to those before. However, this effect is only significant for violent arrests. This study serves as an exploratory start to looking at the relationship between the legalization of marijuana and arrests.

Another study conducted by Morris et al. (2014) examined the passage of state legislation that legalized medical marijuana and crime rates to determine if there was a relationship between the two. Using data on crime rates came from the UCR, they use the seven Part I Offenses for each state from 1996 to 2006. Official US state websites were accessed in order to determine if and when medical marijuana legislation was passed in a state; 11 states were found to have legalized medical marijuana, with years ranging from 1996 to 2006. This was turned to a post-law trend variable to account for any observed changes in crime trends. Several sociodemographic characteristics were used as controls, taken from various official data sources. A fixed-effects panel design was employed to assess whether there were changes in crime rates in states with medical marijuana legalization versus those without. Fixed-effects ordinary least squares regression models with logged dependent variables was used to analyze the data and account for state to state differences. Year fixed-effects were also included for any possible national-level influences on crime. The authors found that medical marijuana legalization was not indicative of increased crime rates, and could be related to lower rates of homicide and assault; also, burglary and robbery rates were unaffected by legalization status.

Maier et al. (2017) take it a step further and ask four different questions with respect to the relationship between the legal status of marijuana, crime, and drug abuse rates. They first look at changes in UCR Part I Offenses from 2010 to 2014 using a longitudinal research design. Using paired-sample t tests, they examined a significant reduction in both types of crime from 2010 to 2014, and used a mixed-model ANOVA to determine if it was related to changes in marijuana laws. They found that this decrease was not dependent on any law change regarding marijuana. The second question they look at dealt with the restrictiveness of state laws on marijuana and crime rates. Using a cross-sectional design and a series of one-way ANOVA tests for UCR Part I crime rates in all 50 states in 2014, they found there to be no significant differences between violent and property crime rates in 2014. However, after employing a Tukey post hoc test, significant differences in drug arrest rates were found between marijuana illegal states and the least restrictive states. For the third part, the authors specifically looked at decriminalized states, those with medical legislation, and those with complete prohibition. They used independent samples t tests which revealed there to be no significant differences in rates of violent and property crime between decriminalized and non-decriminalized states, medically legalized and non-medically legalized states, and marijuana being completely illegal in one state and another where it is not. The last part of the study looked at different levels of legalization with respect to crime rates, and included multiple state level controls as covariates. This covariate data was obtained from the 2015 US Census Bureau and the 2016 Bureau of Labor Statistics for each state. The ANCOVAs, with controls included, suggested that there was not a relationship between a state's crime rates and the state's legal status of marijuana.

Although state level trends and analyses are informative, it assumes that these state-level policies regarding legalization are homogenous across the state; this is not the case as local jurisdictions can choose to adopt bans or other restrictions on marijuana dispensaries (Pacula & Smart, 2017; Dilley et al., 2017). Work conducted by Hunt et al. (2018) takes an approach at a lower aggregation level, looking at county laws in California to determine if there are differences in counties that employ different regulations regarding dispensaries. The authors employ a difference-in-difference approach to examine the changes in dispensary allowance at the county-year unit of analysis. Their findings indicate no impacts from dispensaries on any type of violent crime. However, counties that had local ordinances allowing dispensaries potentially experienced a small decrease in property crime and an increase in DUI arrests. So, it is important to look deeper than at the state level, as there is possible heterogeneity in the laws and policies both between and within states.

2.2.2. Crime Attractors/Generators – Geospatial Methods/Analyses

Within a behavioral geography framework, McCord et al. (2007) examined differences in perceptions of crime and disorder based on criminogenic land uses in a neighborhood. These criminogenic land uses are defined as the presence of crime attractors and generators in that neighborhood. The locations of these crime attractors and generators were found from a variety of sources, such as the Philadelphia Police Department, Pennsylvania Liquor Control Board, and the Philadelphia Department of Human Services Webpage. Part I crime data from January 2001 to June 2002 was also obtained from the Philadelphia Police Department, and perceptions of crime and incivilities information came from the 2003 Philadelphia Area Survey. ANOVA models were run as the basic statistical model, along with kernel density estimation and spatial lag variables. The authors found that individuals living closer to more crime generators perceived their neighborhoods to be more crime ridden and to have more disorder than their neighbors. Similar results were found for people living closer to more crime attractors as well. And was a general consensus, as neighbors within the same area, for the most part, agreed on how much crime was affecting their neighborhoods.

Getting into micro-level analyses, Groff et al. (2010) examined the distribution of crime trajectories of street segments in Seattle; arguing routine activity theory as a micro-level theory, so they focus on patterns at the micro-level such as street segments. They argue that these micro places minimizing the aggregation necessary for analysis, reducing ecological fallacy and reducing the spatial heterogeneity among the units of observation. The authors collected crime incident data from 1989 to 2004 in Seattle, Washington; this included location information for each incident, which was aggregated to specific street segments. The authors determined eight trajectory patterns of crime for these streets through a group-based trajectory analysis: crime free, low stable, moderate stable, chronic high, low decreasing, high decreasing, low increasing, and high increasing. They compared the spatial patterns of these trajectories over time with a series of point pattern statistical techniques and K-functions to account for spatial dependence. The findings indicate heterogeneity alongside homogeneity in crime patterns across the city and that these patterns are not uniform within and across areas. These results also suggest differential processes and mechanisms between crime attractors and generators as well as between street segments for crime in the city.

Bernasco & Block (2011) examined the influence of crime attractors and generators on how they affect the spatial distribution of robberies. They obtained 75,065 crime incidents of street robbery by the Chicago Police Department from 1996 to 1998 for the 24,594 census blocks in Chicago. There were nine types of businesses categorized as crime attractors, with counts collected from marketing information. This information was also supplemented with the presence of local illegal "vice" markets from the Chicago Police Department geocoded incident files. To model the robbery count, they conducted a negative binomial model with spatially lagged versions of several independent variables to estimate any spatial effects. Measures were also calculated to address any residual spatial autocorrelation in the model. The authors found that census blocks with a crime attractor, generator, or offender anchor point within their boundaries had the highest robbery count. Those without, but are bordering a block that does, have a lower robbery count; and those that don't have an attractor, generator, or offender anchor point and lack a neighboring block that also does not have one has the lowest robbery rate.

Examining the presence of businesses in general, rather than focusing on specific types of criminogenic businesses, Steenbeek et al. (2012) look at the role these businesses and employees play in neighborhood disorder through a routine activity and social disorganization framework. From 278 neighborhoods in the Netherlands, they surveyed residents about neighborhood physical and social disorder and measured business presence within those neighborhoods. The authors conducted a three level multilevel analysis model, nesting physical and social disorder within respondents, who then are nested within neighborhoods. Global spatial autocorrelation corrections were included as well as a measure of spatial clustering. With regards to business presence, they found that with a larger total number of business establishments in a neighborhood, there is more physical and social disorder. Neighborhoods with at least one liquor store or bar experience more social disorder than those that do not. Medium-sized and large bars were also found to have a positive effect on social disorder. Unsurprisingly, the authors found neighborhood income to be a moderator for the effects of liquor stores on physical and social disorder, suggesting that this presence is even more detrimental in already disadvantaged areas.

Instead of focusing on criminogenic locations or establishments, Slocum et al. (2013) diverge and examine how structural features of the environment mediate the influence of neighborhood organizations and crime. Boundaries were established using the block-groups from the 2000 US Census, nine general types of organizations were identified within the neighborhoods, and block-group counts of seven UCR crimes from the NYPD were used from 2005-2006. The authors found that organizations are significantly more likely to be located in block-groups with higher levels of crime. The results also suggest that there are no significant relationships between the number of organizations in a block-group and crime, except for a few exceptions. Areas with more organizations that act as bridges to external communities and organizations that are resource providers have negative relationships with violent and property crime. Also, areas with more family and child welfare organizations also have lower counts of property crime as well.

Transitioning from a routine activity theory framework to crime pattern theory, Groff & Lockwood (2014) continue off previous work with street segments and crime and look at how exposure to and distance from criminogenic facilities impact crime. With crime incident data gathered from the Philadelphia Police Department, and facility locations were gathered from a number of sources. Buffer zones of 400, 800, and 1200 feet were established around street centroids throughout the city of Philadelphia, which represents traversable space and to measure distance from a criminogenic facility. A negative binomial regression was used with area-weighted means of disadvantage, stability, and ethnic heterogeneity were included to account for spatial and edge effects. Overall, the authors found support for exposure effects to facilities on crime, depending on the facility type and crime type. This also seems depend on the distance from the facility, as these exposure effects decrease with increasing distance from the street segment.

2.2.3. The Relationship between Alcohol and Marijuana

With the legalization of marijuana it has become more accessible to the public, and has rekindled concerns of its potential health consequences and other negative impacts. And while the effect of changing marijuana laws on marijuana use has been examined in multiple studies, less is known about its effect on the use of other substances (Maxwell & Mendelson, 2016; Vigil et al., 2018; Han, Compton, Blanco, & Jones, 2018; Sarvet et al., 2018). Alcohol in particular has been a substance of interest with regard to these changes in marijuana legalization and subsequent changes in marijuana use. There has been contention on the relationship between alcohol use and marijuana use, and if they are compliments or substitutes to one another. As “compliments”, the effects of alcohol and marijuana would enhance one another; if they were “substitutes”, then alcohol could replace marijuana and vice versa to experience similar effects. If they were “independent”, then one’s effect would not alter the other (Subbaraman, 2016). Although this focus is at the pharmacological level, this concept can also be applied to the effect that alcohol outlets and marijuana outlets may have on crime. The individual effects of alcohol or marijuana outlets may change depending on the presence of the other in the same area.

Several studies have been undertaken to examine whether this complimentary versus substitution effect exists: support has been found for the substitution effect through examining changes in availability, pricing, and laws restricting use by age (Anderson, Hansen, & Rees, 2013; Dinardo & Lemieux, 1992; Chaloupka & Laixuthai, 1997; Crost & Guerrero, 2012). Changes restricting alcohol availability and consumption have seen increases in marijuana consumption and vice versa. However, support has been for a complimentary relationship between the two as well: studies have also found that the same restrictions on alcohol, such as price increases, decreases alcohol and marijuana use (Wen, Hockenberry, & Cummings, 2015; Cerdá et al., 2018; Subbaraman & Kerr, 2015; Williams, Pacula, Chaloupka, & Wechsler, 2004; Pacula, 1998). So, there are studies that provide support for both arguments using similar methods. Subbaraman (2016) conducted a review of the literature, looking at 39 studies and their results to determine whether alcohol and marijuana are compliments or substitutes. In this meta-analysis, it was found that 16 studies supported substitution, 10 supported complementarity, 12 supported neither, and only 1 study supported both. Thus, there is not a consensus for whether the relationship between marijuana and alcohol is complimentary, substitutive, both, or if there is even an effect at all. But what these studies do establish is that this possible relationship between the two should be taken into account and explored further.

2.2.4. Lessons from Alcohol Outlets

The existing literature on the geography and spatial distribution of marijuana outlets has taken several approaches to determine its effect on crime. Notably, a great deal of focus has been on examining how the number and density of marijuana outlets in an area have affected crime rates. But before delving into marijuana outlets, alcohol outlets, which have been studied for much longer and more extensively, should be addressed first; alcohol has long been thought and has since been shown to be associated with crime, particularly violent crime (Parker, 2004; Parker & Auerhahn, 1998). This groundwork is laid out by studying alcohol outlets and crime is important for how studies examining marijuana outlets have been conducted: marijuana and its relationship to crime has often been compared to alcohol, and that they operate similarly. As a result, studies looking at marijuana outlets have taken approaches and methodologies from the alcohol and crime literature for guidance.

Scribner et al. (1995) conducted one of the first studies looking at the relationship between alcohol outlet density and assaultive violence within an environmental framework. They collected assaultive violence data from the UCR at the city level from the California Department of Justice for 1990; this was measured to include criminal homicide, forcible rape, robbery, and aggravated assault. The alcohol outlet data came from active licenses as listed by the California Department of Alcoholic Beverage Control. They used both outlet density per person and outlet density per square mile as two distinct ways to measure alcohol availability; there was also a distinction made between outlets that allowed on-premises consumption and those that were off-premises. A least-squares regression model was used, and the findings suggested that a geographical relationship exists between the density of off-sale alcohol outlets and violence in those areas; the rate of assaultive violence was significantly associated with the density of alcohol outlets.

Later research that continued this was conducted using comparable measures and methodologies to determine if there was a similar geographic relationship between alcohol outlet density with homicide, in particular (Scribner et al., 1999). The authors again looked at densities per person and per square mile and included the distinction between on-premises and off-premises alcohol consumption. This time they took a neighborhood-level approach, using census tract data from New Orleans defined as urban residential areas. A least-squares regression model was used with three sociodemographic covariates: ethnicity, social rank, and lifestyle/urbanicity. They are also geocoded by address, aggregating up to the census tract level. Here, they also found there to be a relationship between off-sale outlet density and homicides, reflecting similar results to their previous study on assaults.

Building off the previous literature Gruenewald et al. (2006) include spatial analyses while looking at alcohol outlet density with respect to assaults and assault rates. The authors gathered the assault data from hospital discharge data from the California Office of Statewide Health and the location of alcohol outlets from the California Alcohol Beverage Control; this information was aggregated up to the zip codes using 2000 US Census data. In this study, a population-based ecological approach is used to assess the effects of alcohol outlets as markers for violent activities. They too, utilize alcohol outlet density to measure alcohol availability, but do so per roadway miles in order to additionally reflect ease of access; using a generalized least squares regression model, with corrections included for spatial autocorrelation, they also found that off-premises outlets were associated with violence and assaults. This is reflective of the previous work, finding support of the relationship between alcohol availability and violence.

2.2.5. Density/Number of Marijuana Outlets and Crime

Now with the focus on marijuana outlets, several studies have taken inspiration from the studies looking at alcohol outlets and replicated their methodologies. These studies have taken this approach of utilizing outlet density and number of marijuana outlets as a way to measure the presence and availability of marijuana within a given area. This is under the assumption that marijuana outlets and alcohol outlets have similar criminogenic processes and mechanisms for facilitating crime.

Using an ecological cross-sectional design, Kepple & Freisthler (2012) examined the impact of medical marijuana dispensaries on crime rates. The location data gathered was aggregated to 2000 US Census tract boundaries and the density of dispensaries were measured per roadway mile for these census tracts. The crime data was measured by police crime incidents in Sacramento City and recoded to UCR definitions. They used geospatial methods to examine ecological relationships between locations and crime; spatial regression analyses were also conducted in order to account for spatial autocorrelation. This was used to determine if the density of marijuana dispensaries was associated with crime rates; this study found that the density of marijuana dispensaries was not significantly related to neighborhood violent or property crime rates and there this is no support for a relationship between medical marijuana dispensaries and crime, at least within the context of this study.

With more of a focus on geospatial analyses, Freisthler et al. (2016) explored changes in the numbers of marijuana dispensaries on rates of crime. From January 2012 to December 2013, crime and Census data was collected for the 333 census blocks in Long Beach, California. This crime data was measured by incident data from the Long Beach Police Department coded to Part I UCR definitions. Locations of dispensaries were obtained through premise surveys supplemented with an official Long Beach city list. The authors used a Bayesian spatial Poisson model with a conditional autoregressive for the spatial analyses to account for a lack of statistical independence among spatial units as a result of spatial autocorrelation. They looked at the number and density of dispensaries within census blocks and found there to be higher rates of both violent and property crime in the areas bordering where there were higher densities of dispensaries. Although these increases were minimal, they suggest that medical marijuana dispensaries may increase crime rates in neighboring areas, but are unrelated in the local vicinity.

Continuing their previous work of how densities of marijuana outlets related to the crime rates of neighboring census blocks, Freisthler et al. (2017) looked at the city of Denver instead. From January 2013 to October 2015, this covers the 481 census blocks in the city and also covers the transition period from medical marijuana dispensaries to the establishment of recreational outlets as well. The crime incident data from the Denver Police Department includes locations, dates, and types of crimes committed. This was coupled with the locations of outlets from the Colorado Department of Revenue Enforcement Division. As with the previous study, a Bayesian Conditional Autoregressive Poisson model was used for the analyses, and they included spatially lagged variables for the adjacent block groups. Similarly, they also found no relationship between densities of outlets to violent and property crime within the census block. However, outlets were positively related to property crime in adjacent census blocks. Overall, the physical availability of outlets does not affect crime within the area they are located in, but rather in surrounding areas.

Chang & Jacobson (2017) took advantage of the closure orders for marijuana dispensaries in June 2010 in Los Angeles to set up a natural experiment to determine whether the closure of a dispensary or it remaining open had any impact on crime rates in the area. They used block level crime data from the Los Angeles Police Department and Sheriff's Department alongside dispensary open/closure data from the Los Angeles City Attorney's Office. The authors employed a Poisson regression model, which allowed for two-way clustering to account for serial correlation at the dispensary level and across dispensaries as well. They found that the closure of dispensaries had an immediate but temporary effect on Part I crimes. However, this effect was also localized to the immediate vicinity of the closed dispensary. There was not strong support for spatial displacement of crime depending on the closure status of these dispensaries, and the results suggest that these mechanisms are not dispensary-specific, but are related to a broad effect of business closures on crime.

An additional study conducted by Brinkman & Mok-Lamme in 2017 examined the short-term effect of marijuana legalization on neighborhood crime. The authors found that the locations of marijuana dispensaries are not randomly allocated across space and neighborhood characteristics: they are more concentrated in areas of higher poverty, higher minority populations, and higher initial employment density. So these dispensary locations and neighborhood attributes are tied in how they affect crime. They control for differential neighborhood characteristics and include measures for outside demand of marijuana tourists through proximity to municipal borders and major roads and highways. An OLS regression with fixed-effects was employed to explore the relationship between marijuana dispensaries and neighborhood crime; a two-stage least-squares approach was subsequently implemented to address any potential biases in the OLS estimates. The authors found that overall effect of adding a dispensary to a neighborhood of 10,000 residents reduces crime by about 17 per month out of an average 90 crimes per month. A majority, 93%, of these reductions in crime is from nonviolent offenses and the decrease in crimes against persons is driven by reduced simple and aggravated assaults. These results are consistent with the assumption that marijuana legalization decreases crime through the displacement of illegal markets. The effects of dispensaries on crime are localized and lack spillover effects into neighboring areas.

2.2.6. Distance from Marijuana Outlets and Crime

Using the density and number of marijuana outlets in an area is not the only method to measure marijuana availability and presence in an area. Several studies have taken an alternative approach and looked at the distance from and around an outlet, and determining whether there is an impact on how far the effect that marijuana outlets have on crime can reach. Rather than using a predetermined area and looking at marijuana outlets within that area, marijuana outlets are instead used as a central location and buffer zones at specified distances from that location are used instead. These varying distances are used to see if the effects that outlets have on crime change as distance from the outlet increases.

Using a routine activity theory framework, Freisthler et al. (2013) examined several characteristics, specifically security measures, of medical marijuana dispensaries and if they are related to crimes around the dispensary. The authors conducted premise surveys in Sacramento, California from December 2010 to February 2011 to find locations of dispensaries and any security measures they used. They also gathered crime data on the number of violent crimes (homicide, assaults, robbery, and aggravated assault) within 1000 feet of a dispensary from the Sacramento Police Department. Using t-tests to compare dispensaries with security measures from those without. Implementing buffer zones of 100, 250, 500, and 1000 feet around the dispensary, the authors found that with security measures, there were significantly lower levels of violence at 100 and 250 feet. Their results found that when comparing medical marijuana dispensaries to one another, those with security measures are more effective at reducing crime within the immediate vicinity of the dispensary. This suggests that the mechanisms for which medical marijuana outlets affect crime rates may not only be based on their presence in an area, but also the security measures that they have in place.

Subica et al. (2018) conducted a GIS buffer analysis on tobacco shops, medical marijuana dispensaries, and off-sale alcohol outlets and looked at how these outlets affected crime around their vicinities. Looking at census tracts in South Los Angeles across eight contiguous zip codes, they gathered spatial outlet data from January 2014 to December 2014. In this time frame, they also obtained crime data, which included the location and type of crime incidents in those areas, which was then recoded using UCR definitions. The authors used a geographically weighted regression model to account for spatial dependencies and to analyze separate localized violent crime regression models for each census tract. They had spatial buffers at 100, 200, 500, and 1000 feet were to gauge how far the effect of these outlets would permeate. They found higher rates of violent, property, and total crime at 100 and 200 feet compared to grocery/convenience stores and community-wide crime rates, but these rates equaled out at 500 feet. Tobacco and alcohol, but not medical marijuana had significantly higher violent and property crime than grocery/convenience stores at 100 feet. For medical marijuana dispensaries specifically, they were related with property crime at the broad census tract level, but not with nearby violent crime.

3. The Proposed Study:

3.1. Background

3.1.1. Marijuana in Washington State

Since there is no consistent federal oversight regarding the legalization of marijuana, each state has employed its own different approach for regulation. Thus the circumstances surrounding marijuana legalization in the state of Washington is unique, and is different from every other state; how medical and recreational marijuana is handled from state to state provides insight to its public health and crime impacts for each respective state. Thus, the background of marijuana in Washington specifically has to be examined, independently from other states and the United States as a whole.

Washington State was among one of the first states in the United States to decriminalize the possession of limited amounts of marijuana for medical uses in 1998 through Initiative 692. However, there was no state agency to regulate the activity of collectives, medical marijuana authorizers or patients; so there were large numbers of medical marijuana dispensaries operating without any oversight. So, the medical marijuana system in Washington was very loosely regulated, if at all. In 2012, Washington became one of the first two states to legalize marijuana recreationally through Initiative 502 (I-502) (Washington State Senate [WSS], n.d.; Dilley et al., 2017). Under I-502, it decriminalized individual possession of small amount of marijuana and allowed for the growing, processing, and retail sales of marijuana. However, possession or use by an individual under the age of 21, driving under the influence of marijuana, home cultivation for recreational use, and use of marijuana in public remain illegal. Also, marijuana establishments cannot be located within 1,000 feet of the perimeter of any elementary/secondary school, playground, recreation center/facility, child care center, public park, public transit center, library, or any game arcade to which admission is not restricted to those 21 and over. However, local governments can pass ordinances to lessen this buffer down to 100 feet except for elementary/secondary school and public playgrounds. Additional restrictions include that marijuana and products may only be sold between the hours of 8 AM and 12 AM and retailers cannot operate vending machines or drive-through facilities (NAMSDL, 2016; Municipal Research and Services Center [MRSC], 2018).

However, in contrast to the previously loose legal medical market, the Washington Liquor and Cannabis Board (LCB) agency developed rules to regulate the retail market. It oversaw the licensing of marijuana growers, processors, and retailers, and it established a maximum number of marijuana retail licenses that would be allowed in each city or county. There was originally a limit of 334 licensed retailers to be allowed to operate in the state and the recreational marijuana retail market became operational in July 2014.This system to regulate recreational marijuana in Washington absorbed the previous medical marijuana system, and in 2015 required medical marijuana dispensaries to become licensed retailers, with a medical-use endorsement if desired. This set the limit of number of retailers allowed to be at 556 dispensaries, allocated geographically across the state (NAMSDL, 2016).

Even within each state that marijuana is legal, there is a large amount of variation in how localities and municipalities control and regulate marijuana. There is some locus of control granted to counties and cities for the regulation of marijuana underneath the overarching state laws. Article XI, Section 11 of the State of Washington's Constitution allows for any city, town, township, or county to make and enforce any laws within their locality that are in concordance with the state laws; so, both city and county governments can regulate marijuana businesses through things such as zoning laws, public health, and police powers (Dilley et al., 2017; MRSC, 2018). This was further addressed in 2014 when Washington State Attorney General Bob Ferguson issued a statement clarifying the extent of local control over marijuana as detailed in I-502. It stated that local ordinances can employ practices that make state-licensed marijuana impractical to operate and are not preempted from banning such businesses (Ferguson, 2014).

Dilley et al., (2017) further examined the differences in how localities handled marijuana regulation in Washington by examining community-level responses to marijuana legalization. They found that 125 cities and 30 counties in Washington had passed ordinances that addressed marijuana out of a total 142 and 39, respectively; 60 entities had enacted a permanent ban on retail sales while 7 had temporary bans. This accounts for approximately 30% of the state population where retail sales are not permitted. 83 entities applied zoning restrictions on retail sales and 10 cities established caps limiting the number of retail businesses in their jurisdictions. 37 cities required a business license to sell marijuana, 5 of which needed marijuana-specific business licenses. The authors also found 35 cities and 5 counties to had imposed additional regulations on buffer zones and hours of operations for retail-marijuana businesses.

Thus there are a multitude of possible models for marijuana markets for each locality, and that there is little consistency across the state with regard to legal marijuana. This work conducted by Dilley et al., (2017) mentioned several motivational factors for this variation. Although I-502 was passed statewide, a majority of the 19 of 39 counties did not pass the measure, and up to 62% in those counties voted against it. So in those areas there might be more restrictive control over the marijuana markets. Another factor is that legalization for retail marijuana is relatively new, and so the public health impacts are largely unknown; however, using the regulation of alcohol and tobacco, then local measures of control are likely to be employed to mitigate potential public health risks. Lastly, the previous loose medical marijuana market could have influenced decisions regarding recreational marijuana, as there was a large growth of dispensaries unlicensed by the state during this time.

3.1.2. The City of Tacoma

Therefore, the environmental and legal characteristics of the City of Tacoma and its outlying neighborhoods are important as they can affect behavior and in turn affect crime. The rules and regulations unique to Tacoma regarding marijuana legalization can influence where retail dispensaries may be located and may consequently influence their surroundings. The physical environmental features of the city include the location of central business districts, commercially zoned areas, other designed land-use areas, and street networks. The social features of the city include the socioeconomic and sociodemographic characteristics of the residents. All of these factors contribute to what makes Tacoma unique and different from other cities in Washington; they contribute to the environmental backcloth of the city and can affect a person's behaviors, awareness spaces, and travel patterns within the city. So it is important to take these features into consideration when examining the spatial patterns of crime in the city.

Tacoma is located in Pierce County in northwestern Washington; it is a port city situated on southern tip of Puget Sound and is 26 miles southeast of Seattle, 25 miles northeast of Olympia, the state capital, and is roughly 40 miles northwest from Mount Ranier National Park ("Tacoma, Washington", n.d.). Tacoma is the third largest city in Washington State and the city center has a mix of suburbs (Parkland, Dash Point, etc.) and other cities (Ruston, Lakewood, University Place, Federal Way, etc.) surrounding it. In 2016, Tacoma had a population of 205,602 and a median age of 36 years; it is 59.7% White, 11.3% Hispanic, and 10% Black, 9% Asian, and 7.5% multiracial. The largest industry sectors in Tacoma are Healthcare and Social Assistance, Retail Trade, and Educational Services. The median household income in Tacoma was $53,553 in 2016. The majority of people in Tacoma drive to commute to work (86.2%); only 4.86% of the population uses public transportation ("Tacoma, WA", n.d.).

The City of Tacoma took advantage of the local authority available to them to regulate marijuana through zoning and land use regulations; there are several regulations imposed to control retail marijuana that are specific to it. Ordinance No. 28343 issued in January of 2016 enacted a six month "temporary moratorium on new marijuana retail uses and the establishment of marijuana cooperatives". Though it does not impact already existing licensed recreational marijuana retailers, new applications for city licenses, land use, building or other development permits would not be accepted nor processed. The reasoning for this was to allow for time to reevaluate the processes and policies regarding marijuana legalization as they were still undergoing changes and revisions at the time (Ordinance 28343, 2016).

This moratorium was subsequently lifted in May 2016 with the passage of Amended Ordinance 28361; in addition to terminating the moratorium, it amended several codes for the Marijuana Use Regulations and Land Use Regulatory Codes for Tacoma. Amendments included reducing the buffer from 1,000 to 500 feet for public parks, recreation center/facilities, libraries, child care centers, game arcades, correctional facilities, court houses, drug rehabilitation facilities, substance abuse facilities, and detoxification centers within the downtown districts from marijuana retailers. The buffer around public transit centers was additionally reduced to 100 feet. The city also required that all marijuana retailers must have a state license and medical endorsement in order to obtain a city license. There is a city imposed limit of 16 retail marijuana stores allowed to operate within the city boundaries (Ordinance 28361, 2016).

There are specific zoning designations for which areas marijuana retailers can be located in Tacoma; retailers can only be located in Commercial Districts, Mixed-Use Center Districts, and Industrial Districts. But even within those districts there are restrictions: in Commercial Districts, retailers are permitted in all uses except for the Transitional District. For Mixed-Use Center Districts, they are permitted in all except for the Residential Commercial Mixed-Use District, Urban Residential Mixed-Use District, and Neighborhood Residential Mixed-Use District. Within Industrial Districts, retailers are not permitted in the Port Maritime & Industrial District (Land Use Regulatory Code, 2018).

So, the locations of marijuana retailers are dependent on these regulations imposed by the city. Marijuana outlets are not randomly allocated in the Tacoma and are restricted to certain areas. These areas may have different characteristics compared to areas in which dispensaries are not allowed. Thus, the spatial patterns of crime around these dispensaries are may be influenced by these regulations and the neighborhood characteristics as well.

3.2. Research questions and hypotheses

Utilizing the crime pattern theoretical framework established earlier, this study looks at whether the presence of retail marijuana outlets has any effect on the spatial patterns of crimes (property crime, violent crime, and more specifically thefts, burglaries, robberies, and assaults) around them. From this premise, there are several research questions with related hypotheses that this study aims to test:

The first research question asks if the presence of retail marijuana outlets in an area is related to crimes in that area. Through the crime pattern theory perspective and applying crime attractors and generators, marijuana outlets would seem to be criminogenic locations and can operate as both crime generators and crime attractors. They would pull in criminal offenders and present criminal opportunities in the area they are located in due to the availability of marijuana. On the other hand, marijuana outlets can serve as crime detractors in displacing illicit drug markets, therefore also displacing crimes related to drug sales. Dispensaries can also act as crime suppressors due to the security measures they employ; according to routine activity theory, they may harden targets, provide capable guardians, and deter motivated offenders and thus may displace crime. So the

first hypothesis is that the rates of crimes would be affected due to the presence of retail marijuana outlets in the areas around them.

The second research question is focused on the neighboring areas: does the presence of a retail marijuana outlet in an area have an effect on the crime rates of its neighboring areas? If the first hypothesis holds true that they affect crimes around them in their area, then there may also be a change in crime in neighboring areas. However, there is also the possibility that changes in neighboring areas can occur regardless of changes in crime in the focal area. So the **second hypothesis is that the presence of a retail marijuana outlet in an area would affect the rate of crimes in neighboring areas, regardless of changes of crime rates in the focal area.**

The next set of research questions and hypotheses deal with the revenue generated by the dispensaries as opposed to the number of dispensaries themselves. This is due to several reasons: relying on the number of dispensaries assumes that they are the same as one another. This may not be accurate, as there can be variation in heterogeneity in how dispensaries operate and the amount of marijuana they sell. They may be large and provide large amounts of marijuana or they may be small outlets. More revenue can indicate more cash and marijuana flowing in and out of a store. So, revenue and number of dispensaries can be measuring different things. Additionally, having a dispensary provides a constant and stable effect, whereas revenue changes. Even in census block with just one dispensary over time, the effect of that dispensary remains constant. On the other hand, revenue can vary over time. Another reason is that a poorly run store that does not generate a lot of revenue can still have security measures and guards that deter criminals. Or it may have no security measures and guards and therefore entice more crime. The same can be said for stores that bring in high amounts of revenue. So, including revenue as a measure takes into account other exogenous factors and variation at the individual dispensary level that can potentially influence crime rates, but are unable to be measured in this study.

Thus, the third research question deals with the quantity of retail marijuana outlets in an area and if crime rates are related to the number of outlets in a given area. With more outlets in an area, there would be more marijuana available. Additionally, the revenue from marijuana sold is included as another way to measure the amount of marijuana available. This research question delves deeper into the relationship between marijuana outlets and crime. Beyond looking at just the presence of marijuana outlets in the first research question, would that effect be greater if there are more outlets present if the first hypothesis holds true? Thus, the **third hypothesis would be that areas with more marijuana sales and larger quantity of retail marijuana outlets would have higher rates of crime than those areas with fewer retail marijuana outlets.**

The fourth research question is concerned with whether the density and quantity of retail marijuana outlets in an area has any effect on its neighboring areas similar to the third hypothesis. If the second hypothesis holds true that the presence of marijuana outlets affect neighboring areas, then would also affect neighboring areas if there are more outlets and more marijuana available. And so, the **fourth hypothesis is that areas with more marijuana sales and larger quantity of retail marijuana outlets would affect the rates of crimes in neighboring areas more than those areas with fewer marijuana outlets, regardless of changes of crime rates in the focal area.**

3.3. Data

To test the above hypotheses, this study uses data gathered from a number of sources; the dependent variable data is incident level crime data available through the city of Tacoma from their open source data portal. The independent variable data comes from the Washington State Liquor and Cannabis Board and the Washington State Department of Revenue Business Lookup. And finally the socioeconomic and demographic control variables included come from the 2017 American Community Survey (ACS) 5-year estimates. These data are combined into a panel dataset to examine changes over the time period across the census block groups.

3.3.1. Dependent Variables

The dependent variables are the crime counts and crime rates within census tracts of Tacoma. This crime data was gathered from The City of Tacoma open source and publicly available data hub; the data is based on the National Incident Based Reporting System (NIBRS) offenses. It contains crime incidents reported to the police from January 2014 to August 2018. Each observation for a crime incident contains the incident number, the type of crime, the date and approximate time it was committed, and the address/intersection in which it occurred. This information was recoded, with the types of crime being aggregated up to property crimes (larceny, arson, burglary, motor vehicle theft, and theft) and violent crimes (simple assault, aggravated assault, robbery, and murder/manslaughter), drug crimes (drug equipment violations and drug/narcotic violations), and other crimes. However, this dataset does not include domestic violence or sexual assault related offenses.

The location information for these incidents were reverse geocoded and aggregated up from an address level to the census block group level using United States

Census Bureau Geocoder (2018) to determine crime counts and rates for each census block group in the City of Tacoma. From the total of 80,678 crimes reported during this time frame, 73,368 crimes were able to be geocoded. Thus 90.939% of all the crimes reported in Tacoma during this time were able to be geocoded and are included in the analysis.

The dataset includes the following dependent variables: the counts and rates of property crime, violent crime (excluding rape), and drug crimes from January 2018 to August 2018 in each census block group. The disaggregated counts and rates for burglary, assault, and robbery were also included as specific crimes of interest.

3.3.2. Independent Variables

The main independent variable of interest is the number of recreational dispensaries within a census tract or a certain area. The location information for these dispensaries was gathered from the Washington State Liquor and Cannabis Board, where they provide an up to date list of licensed dispensaries in the state. This list contains the license numbers of the dispensaries and the taxes, revenue, and sales (in dollars) that each license accrued each month. The names and locations of each licensed dispensary were found through cross checking the license numbers through the Washington State Department of Revenue Business Lookup. This provided the address which the license was held and the date in which it was first issued. It also includes the endorsements held at each location, which are the types of all the licenses held at that location. All of these licenses had retail marijuana endorsements, but some possessed medical marijuana endorsements as well. In addition, it specifies whether it is still open at that location or not.

The location information for these dispensaries were reverse geocoded and aggregated up from an address level to the census block group level using United States Census Bureau Geocoder (2018). In the state of Washington during this time frame there were 516 retail licenses given out to marijuana dispensaries. Of these 516 licenses, 36 (6.977%) were not able to be linked to a business and an address. Of the remaining 480 licenses, 23 were found to be linked to an address located in Tacoma. So, 7.492% of the licenses with known addresses were located in Tacoma, and 4.457% of all licenses in Washington were located with addresses in Tacoma.

The dataset includes the following independent variables: the number of dispensaries within a given census block group or census tract in Tacoma to measure the density of dispensaries in an area, and the amount of money (in dollars) from sales made as a measure of scale. This data is from August 2014, from the first dispensary being opened in Tacoma, to August 2018, the most recent.

3.3.3. Control Variables

Control variables included in the dataset regarding socioeconomic and demographic measures are pulled from the ACS 5-year estimates from 2013 to 2017. The ACS is a survey conducted by the U.S. Census Bureau designed to collect social, economic, demographic, and housing data every year. Each 5-year estimate uses a series of monthly samples from a sample size of about 3.5 million addresses, over the course of 60 months to create yearly updated estimates at the smallest geographic area, the census tract and block group level. The data is collected through three sequential modes, starting with paper questionnaires through the mail, then a phone interview, and finally with personal visits with a Census Bureau interviewer. In 2013, an internet response option was added to reduce costs, and in 2017 the phone interview portion was removed due to low response rates.

The ACS datasets being used for this study are the 5-year estimates for 2013 to 2017. There is one 5-year estimate for each year of interest, and each estimate is compiled and sampled from the previous 5 years. Thus the 2014 data is sampled and collected from 2009 to 2013, the 2014 data is sampled and collected from 2010 to 2014, and so on. Using these estimates means that effects from previous years may be captured in the more recent estimates as there is overlap in sampling for the later 5-year estimates from previous estimates. And so the values of recent years are reflective and dependent of the sampling of previous years; changes from one year to another are influenced from previous years as well. Interpolation could be used for the values from 2013 to 2018, and there would less overlap of years between the datasets. However, using this method would assume a linear trend during this time period, which may not be reflective of actual trends. Using this combination of datasets from 2013 to 2017 provides information at the census block group unit of analysis where there would otherwise be a lack of available data. Additionally there are not large changes in population and population composition due to the unit of analysis being at such a small level, so these potential issues mentioned would not largely impact their use as control variables.

These ACS datasets used collectively have 300 months of collected data from January 1, 2008 to December 31, 2017. The geographic units for these 5-year estimates are at the census block group level. At the census block group level , the control variables are: population, % youths aged 15-24, % males that are 15-24, % females that are 15-24, % vacant housing units, % one person households, % high school graduates, % with income below the poverty line, median household income, % unemployed, and race/ethnicity designations (% White, % Black, % American Indian, % Asian, % Pacific Islander, % other, % multiple races). There is no missing data for these control variables except in the median household income variable; there are 12 missing values total (0.85%) across several census block groups from several years. Those missing values were linearly interpolated using the existing values for those census block groups.

The neighborhood contexts in which marijuana dispensaries are located in are important to consider: it may be due to the presence of marijuana dispensaries that crime rates are affected, or it could be due to the neighborhood characteristics outlined in social disorganization theory that may affect crime rates. Since marijuana dispensaries are not randomly allocated due to zoning regulations and law restrictions, it could be that they are not associated with changes in crime but rather those changes in crime are products of the environment they are placed in. Several studies have looked at the neighborhood characteristics that dispensaries are located in across several states and cities: across multiple studies spanning from Colorado to California, neighborhoods with marijuana dispensaries were more likely to have higher rates of poverty, lower household income, higher minority populations, and a greater density of alcohol outlets (Morrison et al., 2014; Shi, Meseck, & Jankowska, 2016; Brinkman & Mok-Lamme, 2017; Thomas & Freisthler, 2016). Additionally, it was found that these areas had more highway/major road access and were also primarily commercially zoned. These results are interesting in that these neighborhoods with marijuana dispensaries have consistent features across them. So, it may not just be merely the presence of a marijuana dispensary affecting crime, but also these shared neighborhood characteristics; thus, these attributes are important to take into account when examining this relationship.

The number of alcohol outlets in each census block group is also included as control variables. The data for these alcohol outlets was gathered from the Washington State Liquor and Cannabis Board, where they provide an up to date list of licensed alcohol outlets in the state. This data includes the address of where the outlet is located, the date the business opened, and whether they are on-premise or off-premise. The distinction between an on-premise and off-premise outlet is whether alcohol is allowed to be consumed at that location, such as a bar or restaurant (on-premise) versus a liquor store or gas station (off-premise). The location information for these alcohol outlets were reverse geocoded and aggregated up from an address level to the census block group level using United States Census Bureau Geocoder (2018). Of the listed 683 alcohol outlets in Tacoma, 182 (26.647%) were not able to geocoded and therefore not included in the analysis.

Another control variable being included is the presence and number of highways and highway on/off ramps in a census block group. The data for this information was obtained from The City of Tacoma open source and publicly available data hub. It includes a shapefile and data file of all streets in Tacoma. This shapefile was overlaid with a census block group shapefile for Tacoma and joined through ArcGIS software. From there it was determined which census block group had highways running through it and if there was the presence of highway on/off ramps. The data does not include when the roads were built, so these highways and ramps are assumed to have existed throughout the time period of interest, 2013 to 2018. This street data is being used as a proxy of traffic volume in the census block group and also as a proxy for accessibility to marijuana outlets. As a proxy measure for traffic volume, those census block groups with more highways and ramps have more people going through them compared to others without them, there is more potential for victims and offenders to interact. If there are highways and on/off ramps in the vicinity to the dispensary, then it allows for easier access to and from the dispensary for both customers and potential offenders.

3.4. Methods

For this project, several analytical methods will be employed in order to determine the relationship between the presence of dispensaries and crime. First, a simple OLS regression model will be initially employed to determine the relationship between crime and dispensaries. It will be used as a preliminary analysis of the data. Additionally, a correlation matrix will be presented to test for multicollinearity among the explanatory variables. More complex models will then be included to account for several factors and constraints of the data. Moran's I tests will be conducted to determine whether the spatial distribution of the values is a result of random spatial processes or if there is spatial clustering present. If the Moran's I tests suggest that there is spatial clustering and that the distribution is not due to underlying random spatial processes, then a Spatial Durbin Model will be run. A Durbin-Wu-Hausman test will be conducted to determine whether a fixed-effects model or a random-effects model will be the best suited for this analysis. After this determination, the spatial models will be run accordingly. These models will be able to account for spatial clustering and spatial lag effects.

3.4.1. Testing for Spatial Autocorrelation: Moran's I

This study is interested in examining the locations of marijuana dispensaries and their impact on crime in their immediate and neighboring areas. As such, there may be interdependence between these different areas, where the characteristics of neighboring areas may influence one another and their subsequent patterns of crime. This is being taken into account through the use of testing for spatial dependence and spatial autocorrelation between the units (Anselin & Bera, 1998). Spatial dependence is when the value observed in one spatial unit is influenced or depends on the value observed at another neighboring spatial unit. Spatial autocorrelation can be described by how these spatial dependencies may cluster in space depending on their values; positive spatial autocorrelation is when similar values tend to be clustered together in space, whereas negative spatial autocorrelation is when values dissimilar to one another cluster together (Anselin & Bera, 1998).

Thus the concern with spatial autocorrelation is that the effects observed in certain areas may be related to their neighboring areas, weakening explanatory power or significance in the results if not taken into consideration. This also has implications for the violation of assumption in regression modeling; spatial autocorrelation in the residuals violates the assumption that the observations are independent (Bernasco & Block, 2011). This may be due to several reasons such as spatial spillover effects, omitted variables in the model, or measurement errors and unobserved heterogeneity.

The absence of spatial autocorrelation needs to be tested, and the most commonly used test is Moran's I statistic. Moran's I is a measure of global spatial autocorrelation, which reflects the correlation between the residual of a spatial unit and mean residual of all adjacent blocks (Bernasco & Block, 2011). The null hypothesis for the Moran's I test indicates that there is no spatial autocorrelation, and the alternative hypothesis indicates that there is the issue of spatial autocorrelation. In the case that the null hypothesis is rejected at a p-value of 0.05 and spatial autocorrelation is present, the Moran's I statistic and the z-value indicates the direction of spatial autocorrelation: if it is positive then there is positive spatial autocorrelation, and if it is negative then there is negative spatial autocorrelation.

In order to conduct this test a spatial weights matrix first must be created. The spatial weights matrix for this study was created through GeoDa, a geographic information system (GIS) analytical program. It is denoted by W, a N by N matrix, where the columns and rows correspond to the spatial unit observations. In this study, it would be the census block group level, so in this case it would be a 235 x 235 matrix. In this matrix, it expresses for each census block group whether the other census block groups in the dataset are part of its neighborhood set; that is, it is binary indicator where if $w_{ij} = 1$ then i and j are neighbors, and if $w_{ij} = 0$ then they are not (Anselin & Bera, 1998; Anselin, Gallo, & Jayet, 2008). Observations were categorized as neighbors through a Queen's contiguity for adjacency; this categorization labels census block groups as neighbors when the focal census block group shares at least a single point with another census block group (Viton, 2010).

3.4.2. Spatial Modeling: The Spatial Durbin Model

If spatial autocorrelation has been determined to be a concern, there are several methods to address this issue; the most common are spatial lags or error components that are incorporated to reflect these spatial dependencies. A spatial lag is a variable constructed from the weighted average of neighboring observations as determined in the

W weights matrix. These spatial lags can be included in the model by applying it to independent variables, dependent variables, error terms, or a combination thereof (Anselin & Bera, 1998; Anselin et al., 2008).

Where these spatial lags or spatial errors are applied is an important distinction to make due to potential theoretical implications as to where the spatial dependencies lie. A spatial lag of the independent variable, or Spatially-lagged X Model (SLX), assumes that those explanatory variables present in one spatial unit have effects on explanatory variables in other spatial units. Spatial lags applied to the dependent variables, Spatial Lag Models (SLM) or Spatial Autoregressive Model (SAR), would argue that outcomes in one location would be linked to outcomes in other locations. Spatial errors, or Spatial Error Models (SEM), argue that the links between locations arise from the error generation process (Golgher & Voss, 2016; Sarrias, 2017; Steenbeek et al., 2012). The combination of these spatial lags for the dependent variables and error terms is reflected in the Spatial Autocorrelation Model (SAC).

This study will use the Spatial Durbin Model (SDM), also known as the common factor model, as it incorporates spatial lags for independent and dependent variables; there are anticipated relationships in the independent variables between census block groups, such as dispensaries in one census block groups affecting others. And at the same time there are also concerns with crimes in one census block group affecting crimes in another. The other spatial models do not completely address concerns of where these spatial dependencies are located, so the Spatial Durbin Model will be used. Being able to account for spatial dependencies all in the independent and dependent variables, as well as the error terms, would be the best approach, but as noted by Elhorst (2009) at least one of these spatial interaction effects has to be excluded or else their identification parameters will not be identified. The basic Spatial Durbin Model can be seen in the following form:

$$\boldsymbol{Y = pWy + X\beta + WX\gamma + \alpha + \varepsilon}$$

In this equation, *p* is a global spatial autoregressive parameter that measures spatial interdependency: if $p = 0$ then there is no spatial dependency concerns and a regular OLS regression can be used, if $p > 0$ it indicates positive spatial dependence, and if $p < 0$ then there is negative spatial dependence. *W* is the spatial weighting matrix, so *Wy* is the vector of the spatially lagged dependent variables and *WX* is the vector of spatially lagged independent variables. *X* is the independent variable non-spatially lagged independent variable with β as its coefficient. α is the intercept for the model given that all coefficient $\beta = 0$. γ is coefficient for the local spatial effect, and ε is the error term. Since this study is using a panel dataset, the general equation is therefore as follows, with $t = 1, \ldots,$ T (Sarrias, 2017; Belotti, Hughes, & Mortari, 2017):

$$\boldsymbol{Y_{it} = pWy_{-it} + X_{it}\beta + WX_{it}\gamma + \alpha + \varepsilon_t}$$

This equation also includes *i,* which indexes by the location, or census block group. In pWy_{-it}, *-it* is there the area is spatially linked to location *i* but not including *i* at time *t.* Building off of the general form of the aforementioned equation, the final specified model is as follows. It is a panel Spatial Durbin Model with random effect, and includes the main independent variables of interest for this project is as follows:

$$\boldsymbol{Y}_{(crime\ rate)t} = \boldsymbol{pWy}_{(crime\ rate)t} + \boldsymbol{X}_{(dispensaries)t}\boldsymbol{\beta} + \boldsymbol{WX}_{(dispensaries)t}\boldsymbol{\gamma} + \boldsymbol{X}_{(alcohol\ outlets)t}\boldsymbol{\beta} + \boldsymbol{WX}_{(alcohol\ outlets)t}\boldsymbol{\gamma} + \cdots + \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_{\boldsymbol{t}}$$

3.4.3. Fixed-Effects VS Random-Effects

With the nature of panel data, it allows for the observation of between- and within-individual variation in the spatial units. Between-individual variation is when the spatial units may be different from one another, and within-individual variation is that the observations for any individual spatial unit varies. Panel data can account for this individual heterogeneity, but it comes at the cost of dependencies in the error terms: there is inherent dependencies in the data as the error term for one unit will be correlated across time and the error terms for the same time period will be correlated across the spatial units (Dugan, 2010). This issue of dependence in the error term can be addressed through fixed-effects modeling and random-effects modeling.

Fixed-effect models control for the variation across units, so it is based on the variation in the changes within units, not taking into account variation across units. Fixed-effect models assume that each unit's error terms are not correlated with one another and that that the individual specific constant (the fixed-effect) is uncorrelated with the explanatory variable. So, given that these assumptions are met, fixed-effect models are generally consistent and unbiased. However, because it ignores the between-unit variation, it may be inefficient, and it is unable to estimate the effects of time-invariant variables as it absorbs it in the model (Dugan, 2010; Torres-Reyna, 2007; Sun, 2018).

Random-effect models on the other hand assume that the variation across units are random and uncorrelated with the explanatory variables in the model. It relies on the assumption that unobserved heterogeneity is uncorrelated to the explanatory variables and the assumption that between-unit error is independently and identically normally distributed. So there are concerns with it being susceptible to omitted variable bias and being a biased estimate. Random-effect models trade off being more efficient, but less consistent and may be biased, for the ability to observe effects between units (Dugan, 2010; Torres-Reyna, 2007; Sun, 2018).

Fixed-effect models remove the variation between units, which would not allow for the testing of the hypotheses mentioned earlier. Because this study aims to look at not only the changes within spatial units over time but also between the spatial units and how they affect one another, random-effect modeling would be the preferred method here. Therefore, due to the underlying theoretical motivations random-effects models will be used over fixed-effect models.

3.5. Results

3.5.1. Descriptive Statistics

There are 235 census block groups being examined here, across the span of 5 years from 2014 to 2018, resulting in 1,175 observations at the census block group X year level. Across the 5 years within this dataset there are 16 unique census block groups that have had marijuana dispensaries located within them at some point. Tables 1 and 2 below present the descriptive statistics for all the variables used in the analysis.

For the dependent variables for all block groups, the counts of violent crimes range from 0 to 77 per census block group, with a mean of 6.684 and a standard deviation of 11.156. Property crimes range from 0 to 969 crimes committed per census block group with a mean of 42.793 and a standard deviation of 71.237. The number of all crimes ranges from 0 to 1046 per census block group, with a mean of 49.477 and a standard deviation of 80.344. For those census block groups without a retail marijuana outlet located within them, the number of violent crimes ranged from 0 to 72 with a mean of 5.970 and a standard deviation of 9.891. For property crimes it ranged from 0 to 662 with a mean of 37.455 and a standard deviation of 51.085. For all crimes the range was 0 to 713 with a mean of 43.424 and a standard deviation of 59.102. For the census block groups with at least one retail marijuana outlet located within it, violent crimes ranged from 0 to 77 with a mean of 20.448 and a standard deviation of 21.101. For property crimes the range was from 0 to 969 with a mean of 145.603 and a standard deviation of 205.217. For all crimes the range is from 0 to 1046, with a mean of 166.052 and a standard deviation of 223.648.

For the independent variable for all block groups, the number of retail marijuana outlets in a census block group ranged from 0 to 3 with a mean number of 0.060 per census block group and a standard deviation of 0.287. The amount of money from marijuana sales ranged from $0 to $13,515,169 per census block group with a mean of $196,579.20 and a standard deviation of $1,130,744. For those census block groups with at least one retail marijuana outlet located within it, it ranged from 1 to 3 with a mean of 1.224 dispensaries per census block group and a standard deviation of 0.497. The amount of money from marijuana sales ranged from $24,188 to $13,515,169 per census block group with a mean of $3,982,424 and a standard deviation of $3,315,561.

There are several other control variables of interest that should be noted as well: for the number of alcohol outlets, it ranged from 0 to 31 in all census block groups with a mean number of 1.7 alcohol outlets per census block group and a standard deviation of 3.443. The number of on-premise outlets ranged from 0 to 16 with a mean of 0.818 and a standard deviation of 1.491. For off-premise outlets, it ranged from 0 to 22 per census block group with a mean of 0.883 and standard deviation of 2.362. In census block groups without a dispensary, the number of alcohol outlets ranged from 0 to 31 with a mean of 1.521 and a standard deviation of 3.112. The number of on-premise outlets per census block group range from 0 to 9 with a mean of 0.752 and standard deviation of 1.343. The number of off-premise outlets per census block group ranged from 0 to 22 with a mean of 0.769 and a standard deviation of 2.185. In census block groups with at least one dispensary, the number of alcohol outlets per census block group ranged from 0 to 30 with a mean of 5.155 and a standard deviation of 6.464. The number of on-premise outlets ranged from 0 to 16 per census block group with a mean of 2.086 and a standard deviation of 2.958. The number of off-premise outlets ranged from 0 to 14 per census block group with a mean of 3.069 and a standard deviation of 4.039.

For the number of highways and highway ramps, it ranged from 0 to 17 in all census block groups with a mean number of 0.894 per census block group and a standard deviation of 2.111. In census block groups without a dispensary, the number of highways and ramps ranged from 0 to 17 with a mean of 0.799 and a standard deviation of 1.961. In census block groups with at least one dispensary, the number of highways and ramps per census block group ranged from 0 to 10 with a mean of 2.741 and a standard deviation of 3.581.

A note to make when looking at these descriptive statistics is the relatively low number of crimes in census block groups without a dispensary when compared to those census block groups with at least one dispensary. This is especially notable with regard to robberies. This raises concerns with potential effects that may be found in the model. This can result in an unstable series and make it hard to detect an effect. It suggests that there is not a lot of variation in the distribution of robberies. This is confirmed in Figures 1 and 2 which shows that robberies are heavily skewed to the right and are mostly 0s. Thus, there may be potential concerns of spuriousness in the results from the models to be run.

With this focus on robberies, the data was explored further, looking at the number of robberies in those census block groups where there is at least one dispensary. Of the total 1856 robberies committed in all census block groups across the five year time period, 298 of those robberies occurred in a census block group with a dispensary. In those census block groups, 87 robberies occurred on the same block that a dispensary was located; thus, approximately 29.1941% of the robberies in a census block group with a dispensary occur on the same block as that dispensary. This suggests that robberies may be disproportionately occurring closer to dispensaries as opposed to distributed evenly or randomly across the census block group. The occurrence of robberies may be clustered around dispensaries, and can warrant being looked into in the future.

Table 1. Descriptive Statistics for Dependent Variables from 2014 to 2018

Variable	All block groups				Block groups without marijuana stores				Block groups with marijuana stores			
# of census block groups, N (%)*	1,175 (100)				1,117 (95.06)				58 (4.94)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Total number of crimes	49.477	80.344	0	1,046	43.424	59.102	0	713	166.052	223.648	0	1,046
Violent crime	6.684	11.156	0	77	5.970	9.891	0	72	20.448	21.101	0	77
Assault	5.081	8.456	0	64	4.650	7.894	0	64	13.379	13.378	0	46
Robbery	1.581	3.432	0	36	1.301	2.616	0	20	6.983	8.797	0	36
Property crime	42.793	71.237	0	969	37.455	51.085	0	662	145.603	205.217	0	969
Burglary	8.740	9.992	0	100	8.098	8.467	0	77	21.103	22.113	0	100
Theft	27.112	57.291	0	833	23.069	39.860	0	594	104.983	173.219	0	833
Crime rate (per 1,000)	43.618	66.885	0	984.807	39.180	59.034	0	984.807	129.094	126.831	0	510.030
Violent crime rate	5.816	9.556	0	70.677	5.220	8.654	0	70.677	17.311	16.524	0	51.429
Assault rate	4.427	7.325	0	64.662	4.046	6.800	0	64.662	11.767	11.925	0	44.571
Robbery rate	1.372	2.817	0	26.243	1.159	2.406	0	26.243	5.475	5.669	0	18.369
Property crime rate	37.801	59.107	0	914.365	33.960	52.189	0	914.365	111.783	113.013	0	475.426
Burglary	8.054	9.411	0	97.656	7.507	8.341	0	71.823	18.588	18.525	0	97.656
Theft	23.717	47.317	0	820.442	20.949	42.300	0	820.442	77.015	89.661	0	408.726

* This value calculated from number of census block group X number of years, so 235 census blocks by 5 years

Table 2. Descriptive Statistics for Independent and Control Variables from 2014 to 2018

Variable	All block groups				Block groups without marijuana stores				Block groups with marijuana stores			
# of census block groups, N (%)*	1,175 (100)				1,117 (95.06)				58 (4.94)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Population	1283.3	570.2298	361	5,009	1,288.401	574.089	361	5,009	1,185.052	483.800	586	3,537
# of dispensaries	0.060	0.287	0	3	0	0	0	0	1.224	0.497	1	3
Revenue ($)	196,579.20	1,130,744	0	13,515,169	0	0	0	0	3,982,424	3,315,561	24,188	13,515,169
# of alcohol outlets	1.700	3.443	0	31	1.521	3.112	0	31	5.155	6.464	0	30
On-premise	0.818	1.491	0	16	0.752	1.343	0	9	2.086	2.958	0	16
Off-premise	0.883	2.362	0	22	0.769	2.185	0	22	3.069	4.039	0	14
# of highways/ramps	0.894	2.111	0	17	0.799	1.961	0	17	2.741	3.581	0	10
Race/ethnicity												
White	0.676	0.182	0.167	1	0.678	0.183	0.167	1	0.629	0.147	0.295	0.916
Black	0.095	0.088	0	0.520	0.095	0.089	0	0.520	0.101	0.066	0	0.252
Other minority	0.145	0.122	0	0.580	0.143	0.121	0	0.580	0.185	0.140	0.012	0.560
Gender												
Male	0.496	0.063	0.293	0.836	0.495	0.062	0.293	0.836	0.496	0.067	0.344	0.675
Female	0.505	0.063	0.164	0.707	0.505	0.062	0.164	0.707	0.504	0.067	0.325	0.656
Youth aged 15-24	0.141	0.090	0	0.896	0.140	0.091	0	0.896	0.151	0.065	0.037	0.286
Males aged 15-24	0.070	0.050	0	0.375	0.070	0.051	0	0.375	0.064	0.037	0.011	0.150
Females aged 15-24	0.071	0.057	0	0.531	0.070	0.057	0	0.531	0.087	0.055	0.013	0.215
Median household income	57,249.9	23,012.03	12,063	148,500	57,768.17	23,197.08	12,063	148,500	47,268.55	16,272.24	20,042	100,423
High school graduate	0.826	0.153	0.135	1	0.826	0.154	0.135	1	0.840	0.130	0.406	0.978
Unemployment	0.086	0.066	0	0.330	0.086	0.066	0	0.330	0.097	0.060	0	0.234
Below poverty level	0.168	0.126	0	0.695	0.166	0.127	0	0.695	0.215	0.101	0.067	0.451
1 person household	0.133	0.090	0	0..575	0.132	0.091	0	0.575	0.153	0.081	0.022	0.346
Vacant housing units	0.080	0.071	0	0.371	0.080	0.070	0	0.371	0.092	0.092	0	0.369

* This value calculated from number of census block group X number of years, so 235 census blocks by 5 years

Figure 1. The Frequency Distribution of Robberies Occurring in All Census Block Groups

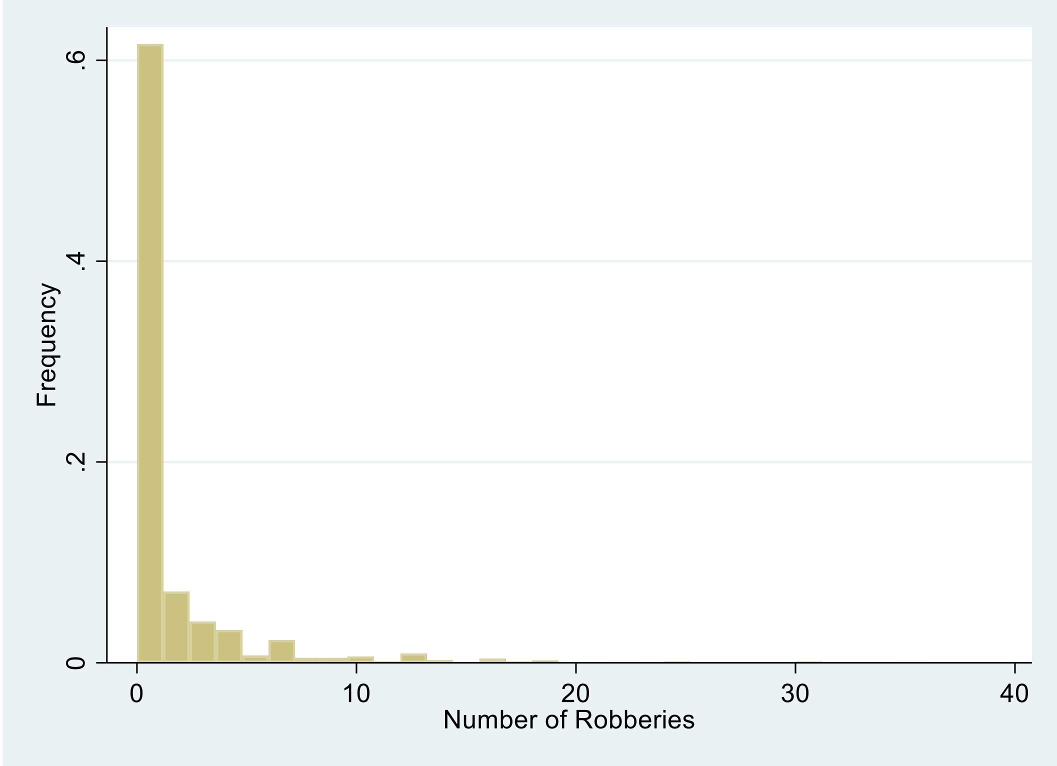
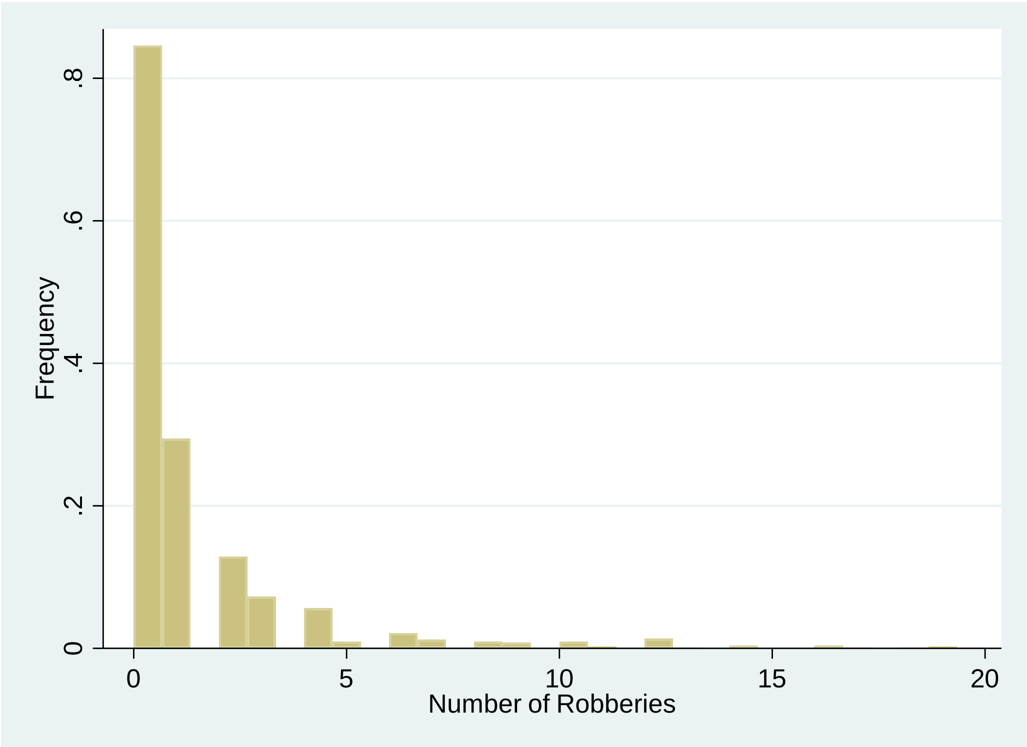


Figure 2. The Frequency Distribution of Robberies Occurring in Census Block Groups Without a Dispensary



A two-sample t-test was conducted to determine if the difference of means for crime rates between the two groups, census block groups without marijuana dispensaries and census block groups with marijuana dispensaries, are significantly significant. Table 3 below displays the results of the t-tests for total crime rate, property crime rate, and violent crime rates: using a two-tailed test, the null hypotheses are that the difference between the groups is 0. For all crimes, the p-values were 0.0000, which are significant at the 0.05 level, thus rejecting the null hypotheses that there is no difference between the groups.

Table 3. Two Sample T-Test Results for Census Block Groups With and Without Dispensaries

	difference in means	t	p-value
Total number of crimes	-122.6274	-12.0041	0.0000
Violent crime	-14.17871	-10.0378	0.0000
Assault	-8.729355	-7.8611	0.0000
Robbery	-5.681953	-13.1637	0.0000
Property crime	-108.1487	-11.9324	0.0000
Burglary	-13.00587	-10.0702	0.0000
Theft	-81.91382	-11.1616	0.0000
Crime rate (per 1,000)	-89.91437	-10.4304	0.0000
Violent crime rate	-12.09118	-9.7656	0.0000
Assault rate	-7.721478	-8.0360	0.0000
Robbery rate	-4.316052	-12.0544	0.0000
Property crime rate	-77.82319	-10.1964	0.0000
Burglary rate	-11.08139	-9.0393	0.0000
Theft rate	-56.06607	-9.0999	0.0000

3.5.2. Correlations

Table 4 below shows the correlation matrix between the key independent variables of interest and the dependent variables. There are moderate and positive correlations between dispensaries and several outcome variables of crime. Dispensaries are moderately correlated with total crime (0.4123), property crime (0.4125), and theft (0.4115). In Table 5, there are additional correlations between control variables of interest and the dependent variables are shown. Alcohol outlets are strongly and positively correlated with total crime (0.6214), property crime (0.5896), theft (0.5776), violent crime (0.6214), assault (0.6248), and robbery (0.5003). On-premise outlets are strongly and positively correlated with total crime (0.5480), property crime (0.5277), theft (0.5211), and violent crime (0.5177). And off-premise outlets are strongly and positively correlated with total crime (0.5598), property crime (0.5262), theft (0.5129), violent crime (0.5790), and assault (0.5918).

These correlations are as expected from the previous literature; the dispensary variable is moderately correlated with the crime outcome variables, which suggests that there exists a relationship between the two, albeit not very strong. The control variables dealing with alcohol outlets are also positively correlated with several crime outcome variables, although their correlations are stronger than the dispensary variable. This is similar to the findings from the previous literature examining the relationship between alcohol outlets and crime. All other variables included in the model did not indicate any moderate or strong correlations with the outcome variables of crime.

Through these correlations there are concerns about multicollinearity between some explanatory and control variables. Dispensaries and revenue are highly correlated with one another, and alcohol outlets, on-premise, and off-premise are correlated with one another. This makes sense, as dispensaries and revenue both measure marijuana availability, and on-premise and off-premise are types of alcohol outlets. After systematically omitting these variables and observing changes in the variance inflation factor (VIF) values to test for multicollinearity, on-premise and off-premise was excluded from the spatial models; alcohol outlets will be used instead as the measure of alcohol availability in the census block group. For theoretical reasons the other variables will be used, and will be included depending on the hypotheses being tested; revenue will be used in place of dispensaries for the third and fourth hypotheses in order to measure total marijuana available. This would be a better measure instead of density or number of dispensaries, as that assumes all dispensaries are homogeneous in their characteristics.

Table 4. Correlation Matrix for Independent Variables of Interest and Dependent Variables

	dispensaries	revenue	total crime	property crime	burglary	theft	violent crime	assault	robbery
dispensaries	1								
revenue	0.7871	1							
total crime	**0.4123***	0.2955	1						
property crime	**0.4125***	0.2886	0.9919	1					
burglary	0.2758	0.2178	0.7625	0.7479	1				
theft	**0.4115***	0.2761	0.9674	0.9837	0.6342	1			
violent crime	0.3026	0.2675	0.8481	0.7902	0.6749	0.7389	1		
assault	0.2373	0.2124	0.7661	0.6983	0.6308	0.6417	0.9748	1	
robbery	0.3941	0.3427	0.8603	0.8396	0.6296	0.8140	0.8386	0.6963	1

* indicates a moderately strong correlation of 0.4 or greater

Table 5. Correlation Matrix for Control Variables of Interest and Dependent Variables

	alcohol outlets	on-premise	off-premise	total crime	property crime	burglary	theft	violent crime	assault	robbery
alcohol outlets	1									
on-premise	0.8276	1								
off-premise	0.9351	0.5749	1							
total crime	**0.6214***	**0.5480***	**0.5598***	1						
property crime	**0.5896***	**0.5277***	**0.5262***	0.9919	1					
burglary	0.4245	0.3650	0.3883	0.7625	0.7479	1				
theft	**0.5776***	**0.5211***	**0.5129***	0.9674	0.9837	0.6342	1			
violent crime	**0.6214***	**0.5177***	**0.5790***	0.8481	0.7902	0.6749	0.7389	1		
assault	**0.6248***	0.4821	**0.5918***	0.7661	0.6983	0.6308	0.6417	0.9748	1	
robbery	**0.5003***	0.4910	0.4192	0.8603	0.8396	0.6296	0.8140	0.8386	0.6963	1

* indicates a strong correlation of 0.5 or greater

3.5.3. Spatial Autocorrelation and Regression

3.5.3.1. OLS Regression

The results of the preliminary OLS regressions run for the independent variables of interest, dispensaries and revenue, are as follows as depicted in Table 6: in the model for the total crime rate, the dispensaries variable was significant at the $p < 0.01$ level with a coefficient of 27.4678. The revenue variable was also significant, but at the $p < 0.05$ level with a coefficient of 0.0449. The other control variables in the total crime rate model that were significant were population, highway ramps, alcohol outlets, on-premise outlets, unemployment, income, high school graduate, one person household, youths aged 15 to 24, males aged 15 to 24, and below poverty. In the model for the violent crime rate, the dispensary variable was not significant, but the revenue variable was significant at the $p < 0.001$ level with a coefficient of 0.0137. The significant control variables in the violent crime rate model are population, highway ramps, alcohol outlets, income, high school graduate, and one person household. In the model for the property crime rate, the dispensary variable was significant at the $p<0.01$ level with a coefficient of 27.9922, but the revenue variable was not significant. The other significant variables in the property crime rate model are population, highway ramps, alcohol outlets, on-premise outlets, high school graduate, one person household, youths aged 15 to 24, males aged 15 to 24, and below poverty.

Moran's I tests were run in Stata for on the residuals of the OLS regressions for each model to determine spatial autocorrelation: for the model on the total crime rate, it has a Moran's I value of 0.1386 and a pseudo p-value of 0.0000. The model on the violent crime rate has a Moran's I value of 0.1348 and a pseudo p-value of 0.0000. The model on the property crime rate has a Moran's I value of 0.1363 and a pseudo p-value of 0.0000. For all of the models the pseudo p-value is less than 0.05, which indicates that the null hypothesis of no spatial autocorrelation present can be rejected. Therefore, it is necessary to account for spatial dependencies in the model and that OLS is not well suited for the analyses. The Moran's I value for all models was positive as well, which indicates positive spatial autocorrelation. So, the rates of crime in one area are positively related to the crime rates in neighboring areas. However, these Moran's I values are relatively weak, indicating a very small relationship between locations and crime rates.

Table 6. OLS Regression Results and Moran's I Test of OLS Regression Residuals

	Model 1: Total crime rate	Model 2: Violent crime rate	Model 3: Property crime rate
Moran's I	0.1386	0.1348	0.1363
pseudo p-value	0.0000	0.0000	0.0000
z-score	8.284	7.851	8.196
Dispensaries	**27.4678****	-0.5245	**27.9922****
Revenue ($10,000)	**0.0449***	**0.0137*****	0.0311
Population	**-0.0208*****	**-0.0033*****	**-0.0174*****
Highway ramps	**3.8503*****	**0.5490*****	**3.3014*****
Alcohol outlets	**3.9799*****	**0.8054*****	**3.1746*****
On premise	**5.3835****	0.3429	**5.0406****
White	17.9786	-0.3067	18.2853
Black	45.5617	6.4223	39.1394
Other minority	46.8007	7.4503	39.3504
Vacancy	-23.0287	2.4035	-25.4322
Unemployment	**-64.6381***	-0.8457	-63.7924
Income ($10,000)	**-3.3289****	**-0.4271****	**-2.9018****
High school graduate	**-32.3218*****	**-4.7809****	**-27.5410****
One person household	**139.654***	**16.6300*****	**123.024*****
Youth 15 to 24	**68.2566*****	2.1148	**66.1417***
Males 15 to 24	**-198.2308***	-9.1967	**-189.0341*****
Below poverty	**-42.5941****	1.1898	**-43.7839****

*****indicates p-value <0.05, **indicates p-value < 0.01, ***indicates p-value < 0.001

3.5.3.2. The Spatial Durbin Model

A Spatial Durbin Model was run due to the presence of spatial autocorrelation, as indicated from the results of the Moran's I test. The results from the Spatial Durbin Model with random-effects for the effect of dispensaries on crime rates are depicted in Table 7. These models give three results: the main effects, which are the overall effects of the model; the direct effects, which are effects of census block groups on themselves; and the indirect effects, which are the spillover or displacement effects that other census blocks have on each other.

In the first model looking at the total crime rate, the dispensary variable has a main effect with a β coefficient of 13.6393, which means that each additional dispensary increases the total crime rate by 13.6393 per 1,000 people holding all else constant. There is a direct effect of 13.9095, which is that each additional dispensary in a census block group increases the total crime rate in that census block group by 13.9095 per 1,000 holding all else constant. Lastly, there is an displacement and spillover effect of -2.6599, which means that with each additional dispensary in a census block group, the neighboring census block groups experience a decrease of 2.6599 in the total crime rate per 1,000 holding all else constant. However, none of these effects are significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, other minorities, income, one-person household, and youths aged 15 to 24. The significant direct (within census block group) effects were for population, highway ramps, other minorities, income, and one-person households. The significant indirect (spillover and displacement) effects were for population, alcohol outlets, and unemployment.

In the second model looking at the violent crime rate, the dispensary variable has a main effect with a β coefficient of 0.4709, which indicates an overall increase in the violent crime rate by 0.4709 per 1,000 people holding all else constant with each additional dispensary. The direct effect with a β coefficient of 0.3496, indicates that each additional dispensary in a census block group increases the violent crime rate in that census block group by 0.3496 per 1,000 holding all else constant. And the indirect, or spillover/displacement, effect with a β coefficient of -3.5252 means that each additional dispensary in a census block group reduces the violent crime rate in its neighboring census block groups by 3.5252 per 1,000 people holding all else constant. The only significant effect here is the indirect (spillover and displacement) effect, which is significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, income, and one-person household. The significant direct (within census block group) effects were for population, highway ramps, income, and one-person households. The other significant indirect (spillover and displacement) effect was only for population.

In the third model looking at the property crime rate, the dispensary variable has a main effect with a β coefficient of 13.2249, which means that each additional dispensary increases the total crime rate by 13.2249 per 1,000 people holding all else constant. There is a direct effect β coefficient of 13.6603, which is that each additional dispensary in a census block group increases the total crime rate in that census block group by 13.6603 per 1,000 holding all else constant. And there is an indirect effect β coefficient of 1.1541, which means that with each additional dispensary in a census block group, the neighboring census block groups experience a decrease of 1.1541 in the total crime rate per 1,000 holding all else constant. However, none of these effects are significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, income, one-person household, and youths aged 15 to 24. The significant direct (within census block group) effects were for population, highway ramps, whites, other minorities, income, one-person households, and youths aged 15 to 24. The significant indirect (spillover and displacement) effects were for population, alcohol outlets, and unemployment.

Table 7. Results of the Spatial Durbin Model with Random-Effects: Coefficients with Robust Standard Errors (in parenthesis)

Model	Total crime rate			Violent crime rate			Property crime rate		
	Main effects	Direct effects	Indirect effects	Main effects	Direct effects	Indirect effects	Main effects	Direct effects	Indirect effects
Dispensaries	13.6393 (10.7607)	13.9095 (10.2824)	-2.6599 (14.8021)	0. 4709 (0.5203)	0.3496 (0.5369)	**-3.5252*** **(1.7842)**	13.2249 (9.3432)	13.6603 (9.8508)	1.1541 (13.4528)
Population	**-0.0229***** **(.0054)**	**-0.0237***** **(0.0053)**	**-0.0133*** **(0.0060)**	**-0.0032***** **(0.0007)**	**-0.0032***** **(0.0007)**	**-0.0015*** **(0.0007)**	**-0.01939***** **(0.0047)**	**-0.0201***** **(0.0046)**	**-0.0121*** **(0.0053)**
Highway ramps	**9.4906**** **(3.2540)**	**9.9073**** **(3.1893)**	0.9914 (3.5659)	**1.1840*** **(0.4855)**	**1.2320**** **(0.4685)**	-0.1943 (0.4095)	**7.9564**** **(2.7228)**	**8.3065**** **(2.6697)**	0.9333 (3.1659)
Alcohol outlets	0.8531 (1.8704)	0.4302 (1.7276)	**-6.0165**** **(1.9155)**	0.3577 (0.1990)	0.3332 (0.1905)	-0.2048 (0.2786)	0.8771 (1.6364)	0.5103 (1.5061)	**-5.4792**** **(1.7196)**
White	33.8598 (17.8989)	34.5142 (17.9140)	8.2664 (33.4015)	1.9755 (3.0170)	1.9235 (2.9522)	-1.5483 (5.2013)	31.7827 (16.5406)	**33.0061*** **(16.5326)**	13.9009 (29.5525)
Black	11.1207 (15.9449)	12.5993 (16.1136)	9.0070 (47.1801)	0.2055 (2.8965)	0.4192 (2.8891)	1.2042 (7.1647)	11.4269 (14.5678)	13.1324 (14.6322)	16.7132 (41.3140)
Other minority	**35.8598*** **(18.6297)**	**39.8747*** **(18.4468)**	67.0379 (43.5418)	7.6382 (4.0110)	7.9603 (4.0491)	5.2857 (6.8532)	28.4372 (16.6017)	**32.1790*** **(16.2171)**	65.1692 (38.1878)
Vacancy	-5.7201 (36.8438)	-7.9544 (35.5295)	-17.4608 (42.9698)	0.1977 (3.5043)	0.4975 (3.4467)	9.6583 (6.6262)	-5.3579 (34.8648)	-7.8953 (33.4203)	-25.0867 (39.0212)
Unemployment	-2.211 (14.9517)	2.3340 (14.3723)	**83.7316*** **(36.4701)**	-1.009 (3.3282)	-0.8226 (3.2045)	1.3226 (5.3217)	-0.3377 (13.0093)	4.0840 (12.6029)	**83.6216**** **(33.1521)**
Income ($10,000)	**-3.0589**** **(0.9512)**	**-3.0511**** **(0.9644)**	-0.1347 (1.916)	**-0.5333***** **(0.1533)**	**-0.5270**** **(0.1525)**	0.0787 (0.2900)	**-2.5205**** **(0.8310)**	**-2.5294**** **(0.8471)**	-0.4651 (1.7300)
High school graduate	17.9696 (14.9137)	17.4215 (14.0289)	-5.1403 (15.2219)	3.3985 (2.3893)	3.3060 (2.3552)	-3.1575 (2.6197)	14.0979 (12.9828)	13.6616 (12.1243)	-1.9254 (13.2717)
One person household	**96.3620**** **(29.1681)**	**96.8924**** **(30.1107)**	-49.5741 (81.0912)	**13.5845*** **(5.7785)**	**14.1919*** **(6.1193)**	1.2927 (8.9052)	**85.0448**** **(25.6474)**	**85.2463**** **(25.8290)**	-50.5845 (73.2005)
Youth 15 to 24	**53.4601*** **(24.7123)**	52.6849 (26.8501)	-30.1246 (94.2800)	5.8358 (4.5185)	5.4396 (4.7630)	-10.9460 (15.0253)	**47.7225*** **(22.2866)**	**47.3671*** **(23.6983)**	-20.4909 (78.2824)
Males 15 to 24	-53.0552 (37.3723)	-57.1553 (40.8369)	-77.0371 (107.2078)	-7.1991 (7.1334)	-6.7834 (7.7336)	11.2397 (21.9764)	-48.0209 (33.7291)	-52.4592 (36.1944)	-88.2626 (86.9767)
Below poverty	-18.7019 (12.3656)	-19.8353 (13.0700)	-1.2476 (29.1412)	-1.0975 (2.5796)	-1.1174 (2.7368)	4.9845 (4.5550)	-18.3277 (10.6880)	-19.5681 (11.1837)	-5.7874 (26.4986)
Constant	36.6375 (31.3203)	-	-	6.2213 (4.8699)	-	-	28.4211 (26.9708)	-	-

*****indicates p-value <0.05, **indicates p-value < 0.01, ***indicates p-value < 0.001

The results from the Spatial Durbin Model with random-effects for the effect of revenue generated from marijuana sales on crime rates are depicted in Table 8. These next models replace the dispensary variable with a revenue variable, as a much of how much marijuana is available in the census block group. As with the previous models, they contain the main effects, the direct within census block group effects, and the spillover and displacement effects.

In the first model looking at the total crime rate, the revenue variable has a main effect with a β coefficient of 0.0190, which means that for every additional $10,000 increase in revenue generated from marijuana sales, there is a 0.0190 increase in the total crime rate per 1,000 holding all else constant. For the direct effect β coefficient of 0.0201, each additional $10,000 increase in revenue from marijuana sales in a particular census block group would increase the total crime rate within that census block group by 0.0201 per 1,000 holding all else constant. Finally, for the indirect, or spillover and displacement, effect β coefficient of 0.0096, each additional $10,000 in revenue generated from marijuana sales in a census block group would increase the crime rate in its neighboring census block groups by 0.0096 per 1,000 people holding all else constant. However, none of these effects are significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, other minorities, income, one-person household, and youths aged 15 to 24. The significant direct (within census block group) effects were for population, highway ramps, other minorities, income, one-person households, and youths aged 15 to 24. The significant indirect (spillover and displacement) effects were for population, alcohol outlets, and unemployment.

In the second model looking at the violent crime rate, the revenue variable has a main effect with a β coefficient of 0.0035. This indicates that for every additional $10,000 increase in revenue from marijuana sales, there is a 0.0035 increase in the total crime rate per 1,000 holding all else constant. The direct effect with a β coefficient of 0.0034 indicates that each additional $10,000 increase in revenue from marijuana sales in a particular census block group would increase the total crime rate within that census block group by 0.0034 per 1,000 holding all else constant. And lastly, the spillover and displacement effect had a β coefficient of -0.0052, which suggests that each additional $10,000 in revenue generated from marijuana sales in a census block group would decrease the crime rate in its neighboring census block groups by 0.0052 per 1,000 people holding all else constant. However, none of these effects are significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, income, and one-person household. The significant direct (within census block group) effects were for population, highway ramps, income, and one-person households. The other significant indirect (spillover and displacement) effect was only for population.

In the third model looking at the property crime rate, the revenue variable has a main effect with a β coefficient of 0.0160, suggesting that for every additional $10,000 increase in revenue from marijuana sales, there is a 0.0160 increase in the total crime rate per 1,000 holding all else constant. There is a direct effect with a β coefficient of 0.0172, meaning that each additional $10,000 increase in revenue from marijuana sales in a particular census block group would increase the total crime rate within that census block group by 0.0172 per 1,000 holding all else constant. For the spillover and displacement effect with a β coefficient of 0.0144, each additional $10,000 in revenue generated from marijuana sales in a census block group would decrease the crime rate in its neighboring census block groups by 0.0144 per 1,000 people holding all else constant. However, none of these effects are significant at the $p<0.05$ level. The only significant main effects were those for population, highway ramps, income, one-person household, and youths aged 15 to 24. The significant direct (within census block group) effects were for population, highway ramps, other minorities, income, one-person households, and youths aged 15 to 24. The significant indirect (spillover and displacement) effects were for population, alcohol outlets, and unemployment.

Table 8. Results of the Spatial Durbin Model with Random-Effects: Coefficients with Robust Standard Errors (in parenthesis)

Model	Total crime rate			Violent crime rate			Property crime rate		
	Main effects	Direct effects	Indirect effects	Main effects	Direct effects	Indirect effects	Main effects	Direct effects	Indirect effects
Revenue ($10,000)	0.0190	0.0201	0.0096	0.0035	0.0034	-0.0052	0.0160	0.0172	0.0144
	(0.0171)	(0.0182)	(0.0281)	(0.0003)	(0.0034)	(0.0044)	(0.0144)	(0.0153)	(0.0249)
Population	**-0.0230*** **	**-0.0238*** **	**-0.0128***	**-0.0030*** **	**-0.0031*** **	**-0.0015***	**-0.0197*** **	**-0.0204*** **	**-0.0116***
	(0.0053)	**(0.0052)**	**(0.0056)**	**(0.0007)**	**(0.0007)**	**(0.0007)**	**(0.0046)**	**(0.0045)**	**(0.0049)**
Highway ramps	**9.4078****	**9.8193****	1.0730	**1.1864***	**1.2343****	-0.1813	**7.8842****	**8.2293****	0.9899
	(3.1966)	**(3.1344)**	(3.7343)	**(0.4831)**	**(0.4631)**	(0.4085)	**(2.6763)**	**(2.6255)**	(3.3196)
Alcohol outlets	1.3225	0.8845	**-6.4140****	0.3462	0.3158	-0.3433	1.3361	0.9602	**-5.7059****
	(2.1428)	(2.0085)	**(2.1151)**	(0.1951)	(0.1873)	(0.2783)	(1.9425)	(1.8089)	**(1.9072)**
White	30.7043	31.6651	9.0499	1.9079	1.8689	-1.2461	29.0605	30.2214	14.1603
	(17.4506)	(17.5058)	(33.5645)	(2.9740)	(2.9410)	(5.1233)	(16.2123)	(16.2217)	(29.9315)
Black	9.7205	11.1819	10.4960	0.0642	0.2705	1.1525	10.1977	11.8780	17.9133
	(15.2987)	(15.4865)	(46.3237)	(2.8980)	(2.8916)	(7.0954)	(14.0276)	(14.0931)	(40.6244)
Other minority	34.6683	**38.4707***	62.5797	7.4572	7.7694	5.0677	27.4144	**30.9644***	60.8882
	(17.8638)	**(17.7685)**	(42.8234)	(3.9718)	(4.0273)	(6.8206)	(15.9510)	**(15.6361)**	(37.5363)
Vacancy	-9.9376	-12.0885	-14.6130	0.4553	0.7659	9.5440	-9.7477	-12.1986	-22.2922
	(37.0265)	(36.7205)	(44.9549)	(3.5264)	(3.4634)	(6.6679)	(34.9165)	(34.4884)	(40.9842)
Unemployment	-4.6837	-0.0328	**89.0359****	-1.2580	-1.0232	2.2461	-2.5971	1.8798	**87.7872****
	(14.2768)	(13.6984)	**(33.8626)**	(3.3047)	(3.1790)	(5.3225)	(12.3220)	(11.9091)	**(30.7710)**
Income ($10,000)	**-3.020****	**-3.0180****	-0.3216	**-0.5188****	**-0.5111****	0.0899	**-2.4991****	**-2.5134****	-0.6390
	(0.9187)	**(0.9365)**	(1.8539)	**(0.1504)**	**(0.1499)**	(0.2931)	**(0.8027)**	**(0.8252)**	(1.6821)
High school graduate	18.7239	17.9689	-6.1682	3.0534	2.9464	-2.9992	15.1426	14.5063	-3.0160
	(15.3047)	(14.2203)	(14.3537)	(2.4631)	(2.3875)	(2.6286)	(13.3179)	(12.2743)	(12.3777)
One person household	**95.7518****	**95.8837****	-49.8600	**13.9510***	**14.5524***	1.3519	**84.0436****	**83.9018****	-50.7686
	(29.3363)	**(30.1955)**	(82.5771)	**(5.7933)**	**(6.1155)**	(9.0227)	**(25.7463)**	**(25.9338)**	(74.5520)
Youth 15 to 24	**54.8074***	**53.7924***	-30.3257	5.9477	5.4910	-11.8464	**49.0883***	**48.5594***	-19.9407
	(25.1218)	**(27.3032)**	(102.5604)	(4.5505)	(4.7644)	(14.9752)	**(22.6340)**	**(24.1909)**	(86.7257)
Males 15 to 24	-53.4628	-57.7152	-83.7675	-7.2387	-6.7943	11.8212	-48.5785	-53.2073	-95.1695
	(36.2859)	(39.7137)	(105.9552)	(7.0811)	(7.6323)	(20.7437)	(32.6808)	(35.2188)	(87.4549)
Below poverty	-18.9593	-20.0166	-0.8194	-1.1238	-1.1147	5.6508	-18.5427	-19.7385	-6.0002
	(12.6527)	(13.1934)	(29.1949)	(2.5813)	(2.7312)	(4.5595)	(10.9690)	(11.3908)	(26.8304)
Constant	39.1851	-	-	5.9229	-	-	31.2044	-	-
	(31.0792)			(4.8200)			(26.6881)		

*****indicates p-value <0.05, **indicates p-value < 0.01, ***indicates p-value < 0.001

The results for more specific rates of crimes of interest for assault, robbery, burglary, and theft are shown in Table 9 below. Included in the table are the effects of dispensaries and revenue on these crime types. As with the other results, the main effects, direct effects, and indirect effects are included. For all of these specific crimes of interest, there are no significant results, with the exception for the robbery rate. Robbery rate is significant for both the dispensary variable and the revenue variable for main effects and direct effects, but not for the spillover and displacement effects.

For the dispensary variable, the main effect was significant at the $p < 0.01$ level with a β coefficient of 0.9288, meaning that for each additional dispensary, there was an overall increase in the robbery rate by 0.9288 per 1,000 people holding all else constant. The direct effect was also significant at the $p < 0.01$ level with a β coefficient of 0.9284. This indicates that for each additional dispensary in a census block group, that census block group would anticipate seeing a 0.9284 increase in robberies per 1,000 people holding all else constant.

For the revenue variable, the main effect was significant at the $p < 0.05$ level with a β coefficient of 0.0028, so that for each $10,000 increase in revenue from marijuana sales, there would be an increase in the robbery rate of 0.0028 per 1,000 people holding all else constant. The direct effect was also significant at the $p < 0.05$ level with a β coefficient of 0.0029. This suggests that for each additional $10,000 made in revenue from marijuana sales in a census block group, that census block group would see a 0.0029 increase in robberies for 1,000 people.

Table 9. Results of the Spatial Durbin Model with Random-Effects: Coefficients with Robust Standard Errors (in parenthesis)

Model	Dispensaries		Revenue ($10,000)	
	β	Robust Standard Error	β	Robust Standard Error
Assault rate				
Main effects	-0.3858	(0.5052)	0.0009	(0.0022)
Direct effects	-0.4682	(0.5226)	0.0009	(0.0023)
Indirect effects	-2.6063	(1.463)	-0.0039	(0.0039)
Robbery rate				
Main effects	**0.9288****	**(0.3012)**	**0.0028***	**(0.0013)**
Direct effects	**0.9284****	**(0.3101)**	**0.0029***	**(0.0013)**
Indirect effects	-0.5269	(0.5269)	-0.0009	(0.0011)
Burglary rate				
Main effects	1.4356	(1.0191)	0.0026	(0.0023)
Direct effects	1.4336	(1.0615)	0.0024	(0.0025)
Indirect effects	-0.6528	(2.7822)	-0.0057	(0.0062)
Theft rate				
Main effects	10.7839	(9.0661)	0.0083	(0.0116)
Direct effects	11.1186	(9.4044)	0.0091	(0.0121)
Indirect effects	1.0733	(10.5372)	0.0145	(0.0173)

*****indicates p-value <0.05, **indicates p-value < 0.01, ***indicates p-value < 0.001

3.5.4. Sensitivity Analyses

Two sensitivity analyses were conducted to test the robustness of the results found in the models: the first was to include an interaction term between marijuana dispensaries and alcohol outlets, due to the potential relationship between marijuana and alcohol. From the literature, there is evidence to support some sort of relationship between the two, as compliments, substitutes, or both. So, the interaction term between the two is to gauge whether the effects of dispensaries may be dependent on the presence of alcohol outlets and vice versa. The second sensitivity analysis was a comparison of the random effects models to the fixed effects models. The models being run are random effects, but testing whether a fixed effect model results in similar conclusion is important to consider. As mentioned earlier, there are trade-offs between using the two models, and if the results are not similar, the argument for one model over the other can be made.

3.5.4.1. Interaction Terms

While the models previously run include the effect of marijuana dispensaries and alcohol outlets separately, the effect of both together is something that is interesting as well. As mentioned, there has been evidence to support that alcohol and marijuana are related in some way; they may be compliments to one another, substitutes, or both. Therefore, the effect of both retail marijuana outlets and alcohol outlets combined will be tested through an interaction term of their individual measures. The results from the Spatial Durbin Model with the interaction term included are shown in Table 10 below. As with the other models, the main effects, direct effects, and indirect effects are included.

For the indirect, spillover or displacement, effects, there were no significant effects found for the interaction terms. However, in the new model with the interaction included there were significant spillover and displacement effects found of alcohol outlets for the total crime rate, property crime rate, and theft rate. For the total crime rate, it was a significant effect at the $p < 0.01$ level with a coefficient of -5.6338 and a standard error of 2.1042. This means, holding all else constant, the effect of having additional alcohol outlet in a census block group decreases the total crime rate in neighboring census block groups by 5.6338 per 1,000 people. The property crime rate was also significant at the $p < 0.01$ level, and it had a coefficient of -5.1358 with a standard error of 1.9169. So the property crime rate decreases by 5.1358 per 1,000 people in neighboring census block groups from an additional alcohol outlet in a census block group. Lastly, the theft rate was significant at the $p < 0.05$ level with a coefficient of -2.9831 and a standard error of 1.3255. Thus holding all else constant, having an additional alcohol outlet in a census block group decreases the theft rate in surrounding census block groups by 2.9831 per 1,000.

For the overall main effects, the significant effects for the interaction terms found were for the total crime rate, property crime rate, and theft rate. The main effect for the total crime rate was significant at the $p < 0.01$ level, with a coefficient of 1.2858 and a standard error of 0.4040. This means, holding all else constant, the effect of having an additional marijuana dispensary and an additional alcohol outlet in a census block group increases the total crime rate by 1.2858 per 1,000 people. The property crime rate was also significant at the $p < 0.01$ level, and it had a coefficient of 1.2201 with a standard error of 0.3697. So the property crime rate increases by 1.2201 per 1,000 people from having an additional retail marijuana outlet and an additional alcohol outlet together in a census block group. The theft rate was significant at the $p < 0.001$ level with a coefficient of 1.2031 and a standard error of 0.2996. Thus holding all else constant, having an additional marijuana dispensary and an additional alcohol outlet together in a census block group increases the theft rate by 1.2031 per 1,000. Finally, the overall main effects were also significant for alcohol outlets and the robbery rate. It was significant at the $p < 0.01$ level with a coefficient of 0.1760 and a standard error of 0.052. This means that holding all else constant, the robbery rate increases by 0.1760 per 1,000 for each additional alcohol outlet.

The direct effects, or effects within census block groups, found significant effects for the total crime rate, property crime rate, and theft rate as well. The direct effect for the total crime rate was significant at the $p < 0.01$ level, with a coefficient of 1.3244 and a standard error of 0.4364. This means, holding all else constant, the effect of having an additional marijuana dispensary and an additional alcohol outlet in a census block group increases the total crime rate by 1.3244 per 1,000 people. The property crime rate was also significant at the $p < 0.01$ level, and it had a coefficient of 1.2566 with a standard error of 0.3968. So the property crime rate increases by 1.2566 per 1,000 people from having an additional retail marijuana outlet and an additional alcohol outlet together in a census block group. The theft rate was significant at the $p < 0.001$ level with a coefficient of 1.2265 and a standard error of 0.3134. Thus holding all else constant, having an additional marijuana dispensary and an additional alcohol outlet together in a census block group increases the theft rate by 1.2265 per 1,000. Lastly, the direct effects were significant for alcohol outlets and the robbery rate as well. It was significant at the $p < 0.001$ level with a coefficient of 0.1727 with a standard error of 0.0477. So, for each additional alcohol in the census block group, then the robbery rate would increase in that census block group by 0.1727 per 1,000 people.

There are several interesting findings from these results: in the model without the interaction term included, the only significant effects were the indirect effect of dispensaries on violent crime rates, main effect of dispensaries on robbery rates, and direct effect of dispensaries on robbery rates. However, in this new model with the interaction term, dispensaries were not significant at all for any effects. For the interaction terms, there are multiple significant effects for the total crime rate, property crime rate, and theft rate. Thus, this suggests that dispensaries only have an effect on those crime rates when there is also an alcohol outlet present in the census block group; without the presence of an alcohol outlet, then the effect of a dispensary on crime rates is weakened. This is interesting in how the significant effects are different in this model compared to the one previously run. It would be worth exploring this further and gathering more data on alcohol outlets to supplement the data on marijuana dispensaries.

Table 10. Results of the Spatial Durbin Model with Random-Effects for Dispensaries X Alcohol Outlets: Coefficients with Robust Standard Errors (in parenthesis)

Model	Dispensaries X Alcohol Outlets		Dispensaries		Alcohol Outlets	
	β	Robust Standard Error	β	Robust Standard Error	β	Robust Standard Error
Total crime rate						
Main effects	**1.2858****	**(0.4040)**	0.6134	(8.2886)	-0.3889	(1.9456)
Direct effects	**1.3244****	**(0.4364)**	-0.2295	(8.9582)	-0.6428	(1.8646)
Indirect effects	0.6038	(1.1915)	-11.1649	(26.9871)	**-5.6338****	**(2.1042)**
Property crime rate						
Main effects	**1.2201****	**(0.3697)**	0.8643	(7.8878)	-0.2320	(1.6576)
Direct effects	**1.2566****	**(0.3968)**	0.2349	(8.4894)	-0.4579	(1.5870)
Indirect effects	0.6016	(1.0705)	-7.3527	(24.1673)	**-5.1358****	**(1.9169)**
Violent crime rate						
Main effects	0.0275	(0.0439)	0.2025	(0.7001)	0.3305	(0.2203)
Direct effects	0.0277	(0.0456)	0.0390	(0.7382)	0.3249	(0.2047)
Indirect effects	-0.0357	(0.1205)	-3.2039	(2.3854)	-0.1533	(0.2800)
Assault rate						
Main effects	0.0078	(0.0363)	-0.4513	(0.6174)	0.2648	(0.1739)
Direct effects	0.0069	(0.0374)	-0.5584	(0.6396)	0.2704	(0.1618)
Indirect effects	-0.0593	(0.0935)	-1.9475	(1.9484)	0.1072	(0.2348)
Robbery rate						
Main effects	0.0055	(0.0220)	0.8704	(0.4800)	**0.1760****	**(0.0520)**
Direct effects	0.0065	(0.0226)	0.8321	(0.4946)	**0.1727*****	**(0.0477)**
Indirect effects	0.0130	(0.0330)	-0.8556	(0.7465)	-0.1499	(0.0813)
Burglary rate						
Main effects	-0.0788	(0.0552)	2.2098	(1.2684)	0.2156	(0.1953)
Direct effects	-0.0805	(0.0604)	2.1355	(1.3486)	0.1945	(0.1878)
Indirect effects	-0.0662	(0.1898)	-0.0303	(3.6304)	-0.4565	(0.3921)
Theft rate						
Main effects	**1.2031*****	**(0.2996)**	-1.4743	(6.8953)	-0.0154	(1.3564)
Direct effects	**1.2265*****	**(0.3134)**	-1.9208	(7.1999)	-0.0881	(1.2880)
Indirect effects	0.6531	(0.8394)	-7.9978	(19.8128)	**-2.9831***	**(1.3255)**

*****indicates p-value <0.05, **indicates p-value < 0.01, ***indicates p-value < 0.001

3.5.4.2. Fixed Effects vs Random Effects

The models being run in this project are based on random effects, but there lies the argument that a fixed effect model may be more beneficial. The fixed effect model is more consistent and less biased than the random effect model, and is able to explain more of the variation due to its control of time-invariant variables. So, versions of the models will be run using fixed effects rather than random effects to determine if there are any notable differences between the two models.

After running the models again, but using fixed effects instead of random effects, the results between the two were compared and it was found that they were very similar to one another. In both models the main and direct effects of dispensaries for robberies were significant in both models. The coefficients between the two models were very similar as well. However, there was no indirect effect found for dispensaries on violent crime rates in the fixed effect model, whereas it was significant for the random effect model. Using the revenue variable instead of the dispensary variable and fixed effects instead of random effects, the same results were found: only the main effects and direct effects for the robbery rate were significant.

Thus, when comparing the two, the random effects model and the fixed effect model produced the same results, with the exception of the indirect effect for dispensaries on the violent crime rate. This suggests that due to the similarity in results produced by both models, using either random effects or fixed effects would be appropriate, as there is not a substantial difference between the two.

3.6. Discussion

For the first hypothesis, we do not find support that dispensaries affect overall crime rates in the neighborhoods they are located in when looking at the main and direct effects as produced from the models. However, it is noted that when looking at specific crime types that there is an effect with respect to robberies and that they increase slightly in areas with dispensaries added. This seems to suggest that while aggregate crime rates may not be affected by the addition of dispensaries, they may have an effect on certain crimes like robberies. From a routine activity perspective, this may be attributed to the nature of robberies and characteristics of marijuana dispensaries, as the abundance of marijuana and cash in a dispensary makes it a prime target. In addition, the individuals going to these dispensaries may prove be a prime target as well since they are entering with cash and leaving with marijuana. Similarly, crime pattern theory would argue similar reasons for why neighborhoods would see an increase in crimes; offenders would flock to these neighborhoods, knowing these opportunities existed due to a dispensary being opened, or the intersection of many more possible offenders and victims meeting as a result of dispensaries providing a context to interact.

We find mixed support for the second hypothesis that adding a dispensary in a neighborhood would affect the crime rates in its adjacent neighborhoods. From the indirect (spillover and displacement) effects produced by the model, only violent crime rates were significant in being affected by the implementation of a dispensary, although total crime rates and property crime rates did not. The β coefficient of -3.5252 indicates a negative relationship between dispensaries in an area and its neighbors' violent crime rates; adding a dispensary in a neighborhood would decrease the violent crime rate in neighboring areas by 3.5252 robberies per 1,000 people. This is interesting, and could be attributed to several reasons: from both a routine activity and a crime pattern perspective, crimes may be displaced from neighboring areas to the focal area if there is a dispensary there. Offenders may be drawn to commit crimes that neighborhood with a dispensary in it, thus committing less crimes in other areas. This can be due to a dispensary being an attractive target under routine activity or that a dispensary has certain characteristics that may draw offenders in, although there does not seem to be evidence of an increase in the area that the dispensary is located in. When looking at specific types of crimes, there was no support for any spillover or displacement effects. Thus, this seems to suggest that although violent crime rates for neighboring census block groups are affected by the presence of marijuana dispensaries, it is not necessarily the case when broken up by a specific crime type.

For the third hypothesis, we do not find support that the amount of marijuana available, as measured through revenue, affects crime rates within the same census block group. The models with total crime rates, violent crime rates, and property crime rates did not yield any significant main effects or direct effects. But similar to the first hypothesis, when looking at robbery as a specific crime type, there were significant positive main effects and positive direct effects. These findings give more insight into this relationship between robberies and marijuana dispensaries and suggest that in addition to the presence of a marijuana dispensary, the amount of marijuana available as has implications for robbery rates. With more marijuana available and being sold in a given neighborhood, that neighborhood would also experience slightly more robberies. The underlying theory behind this is similar to that mentioned earlier: with more marijuana available, there are more targets for offenders. This also implies that more marijuana is being sold, and so cash is being exchanged and more potential targets going in and out of these dispensaries.

For the fourth hypothesis, we do not find support that the more marijuana that is available affects crime rates in the neighboring areas. The indirect (spillover and displacement) effects for total crime rates, violent crime rates, and property crime rates were all insignificant. And when looking at more specific crime types, there was also no support that it was significantly related to crime rates. So, these results suggest that the amount of marijuana availability in one area has no impact on the surrounding areas. Contrasted with the mixed support for the previous hypothesis, it seems that the effect of marijuana availability is constrained to the area where that marijuana is available.

So on the whole, these findings suggest two possible conclusions: first, the presence of retail marijuana dispensaries and the amount of marijuana available may not be associated with changes in neighborhood-level crime rates. There was a lack of support for any relationship between marijuana dispensaries and revenue for total crime rates and property crime rates. There was no significant relationship for marijuana dispensaries and revenue with violent crime rates, with the only exception being between dispensaries and spillover effects. This is particularly interesting since there was a relationship between marijuana dispensaries and violent crime rates for spillover and displacement effects, but none for the specific violent crime types despite that robbery had main and direct effects. These findings seem to suggest the alternative conclusion: that the relationship between marijuana dispensaries and neighborhood crime may be more complex beyond the scope of this study. There are several measures that this study did not include, and there are other possible considerations that were not addressed but will be noted for future research. With that said, this study did find small effects on crime in both the neighborhood the dispensary was added and its surrounding neighborhoods.

3.6.1. Limitations

The findings from this study must be taken with several considerations in mind, and has several limitations: first, there are also additional exogenous factors and variables of interest that are not yet included in the dataset: the number of other known crime generators/attractors in the area and their locations would be included to account for the influence that they would have in that area. Alcohol outlets are included here, but there are other crime generators and attractors that are not. It would be important to know the presence/number of these other crime attractors/generators in the area and how far they are located from dispensaries to be able to account for their effects on crime. There are additional control variables of interest that can be included that may be influential, such how much of the census block group is commercially zoned and its population density.

Secondly, there is the assumption that dispensaries are homogenous on several characteristics which may not necessarily be true; accessibility is measured through a proxy with the highway ramp variable, and scale and size are accounted for through the revenue generated by dispensaries in the census block groups. But this study lacks the ability to differentiate between individual dispensaries on factors such as security measures. There is no measure of the presence of security measures and what they are, such as security cameras, security guards, barred windows, reinforced doors, etc. Additionally, the characteristics directly in the vicinity of the retail outlet are unknown, such as other adjacent buildings or lots or how isolated the outlet is. Those immediate features can influence the vulnerability or how much protection an outlet has against victimization and are not consistent from dispensary to dispensary.

In addition, given the state of regulation of medical marijuana in Washington, there is also very limited data on medical marijuana dispensaries in Washington before recreational legalization. With recreational legalization came a tracking system and stricter laws regarding regulation that medical marijuana was eventually added into. Not having this information on medical marijuana dispensaries is concerning on several fronts: first, the lack of regulation of medical marijuana meant that there were very few restrictions in providing marijuana to the public. The loose regulations and lack of oversight allow for people to obtain marijuana similarly to the current recreational system. Thus, it could be possible that the change resulting from the legalization of recreational marijuana may only be symbolic and not reflective of actual changes in the availability of marijuana. Additionally, if those medical marijuana outlets obtained recreational licenses, they could be still operating in the same location and have effects in that area before the scope of this study, and so changes over time may not be observed or as strong as predicted; then, it would not be accurate to say that a recreational marijuana outlet was introduced to the area, but rather that a marijuana outlet was already in place and just that it nominally changed.

Also, there are no measures/variables to control for where marijuana outlets are allowed to be located. They are restricted to certain zones and prohibited in others in the city of Tacoma due to zoning regulations thus, the locations of these retail marijuana outlets are not randomly distributed. This study does not have measures for this and does not have a variable to account for that. There are possible exogenous contributing factors that are not taken into account in this study and may underlie the marijuana dispensary distribution, and therefore the subsequent possible relationship with crime. Along a similar vein, it is unknown what the marijuana outlet replaced. Due to the limited area in which they can be located they may be replacing old medical dispensaries or other similarly restricted facilities; the inclusion of this information is important to know if the outlet took the place of something that was similar to a vacant lot or alcohol outlet, which are criminogenic and attract crime, as compared to something that would deter and suppress crime. So this distinction would be informative to know how marijuana outlets affect crime relative to the previous business or structure it replaced.

Finally, this study is localized to the City of Tacoma in Washington and is unique to their implementation of marijuana legalization, thus there are issues with generalizability. As mentioned earlier, there is high variability in the implementation of recreational marijuana legalization both across and within states, so the findings from this study cannot be generalized to the state of Washington and to the United States as a whole.

The models produced three significant effects for the main independent variables out of a potential total of 14. Even so, these significant effects are relatively weak and did not have large effects on the crime rate; thus, there is a small number of relatively weak effects, which raises the concern that due to the sheer number of models run for the many variables that some significant effects would be found. It is possible given that enough models are run, then a significant effect would eventually be found. And as mentioned earlier, there are relatively low numbers of census blocks with dispensaries; plus, there are low numbers of crimes being committed, particularly violent crimes and robberies which are where the significant effects are found. All of this suggests that although informative, these findings should not be taken at face value and have potential shortcomings.

3.6.2. Future Directions

Despite these limitations, this study provides a direction for future research to explore as marijuana is being legalized in more states and potentially at the federal level. This study focused on the presence of a dispensary in a neighborhood measured by census block groups, but it may be informative to examine the effects on crime rates from a distance based approach. There have been several studies that have looked at crime rates at varying distances from a dispensary, and it may provide a better understanding of dispensary effects on crime rates at a more localized level. However, these studies have taken a routine activity theory approach to this effect, and applying crime pattern theory may be better suited to this distance-based distinction since it emphasizes the environmental characteristics and can account for other nearby crime attractors or generators. The preliminary findings from the study have also indicated that robberies may be more disproportionately occurring near dispensaries, and this study is not able to observe that potential affect. So conducting alternative models and looking into other crime types at this distance based approach can be an informative next step.

This study examined changes on a year-to-year basis, but there are potential changes at finer temporal units that can be of interest. Future work can examine whether there are patterns when looking at different temporal units, such as on a monthly, quarterly, or seasonal level. April 20th, or 4/20, is celebrated as the unofficial holiday for marijuana users due to its resemblance to the number 420, so it would be expected that there would be increased activity at retail outlets around this time with users buying more marijuana. Seasonality is another can also have differential effects on retail outlets; it can affect cultivation, production, and supply of marijuana, as it comes from the hemp plant, so there may be optimal times of the year for cultivation as the plant requires certain growing conditions. Supply may change during the course of the year, which would affect prices and subsequently potentially affect activity at the dispensary. Having more fine-grain temporal units can get at these types of variation that is otherwise unobservable at the annual level.

Another step that we hope to take in the future is similar to the work by Change and Jacobson (2017); as mentioned, they used the closings of dispensaries to examine if that had an effect on crime rates. The data available in this study does have indications for the closing of dispensaries, through the cessation of revenue being generated. Future work with this looking into the not only the addition of a dispensary but also taking it away can provide additional insight to how crime rates may shift. This would provide a deeper understanding on the effect of closures, as the Chang and Jacobson (2017) study only had information on closings and were not able to account for when the medical dispensary opened whereas the data used here has both the information on opening and closing of retail marijuana dispensaries.

3.6.3. Conclusions

This study aimed to expand the literature regarding the relationship between marijuana dispensaries and crimes using spatial methods; the use of spatial methods would be able to account for differences in locations, and be able to examine the effect of a retail marijuana outlet along several domains. We find mixed support for the proposed hypothesis on the relationship between marijuana dispensaries and crime rates in neighborhoods. We do not find many significant associations between marijuana dispensaries and sales with crime rates, with the exception of spillover effects for violent crime for marijuana dispensaries and a within census block group effect for robberies. The results indicate small effects on crime both in the immediate neighborhood and surrounding neighborhoods that are associated with the addition of marijuana dispensaries:

These findings still provide insight into the effect of marijuana outlets and crime, and suggest that it is not as clear cut as it is thought to be. With new legislation being created to keep up with the legalization of marijuana, these findings can set the groundwork for policies controlling the establishment of marijuana outlets within communities as to have the least possible negative impact. And so, the concern with marijuana outlets is likely to be enduring, as the prevalence of marijuana outlets are increasing with the changing laws legalizing marijuana.

That being said, the policy implications that can be drawn from this study suggest that there are no negative effects from adding a dispensary to a neighborhood at this juncture. The negative effects of dispensaries on crime found in this project although present, are small, and are not substantial enough to raise concern on where or how they should be implemented. The findings also suggest that there is a potential for there to be slightly beneficial outcomes from adding marijuana dispensaries to an area. However, the results of this study do not indicate a strong effect in either direction from the addition of marijuana dispensaries in neighborhoods; there are neither substantial increases nor decrease in crime rates after the implementation of marijuana dispensaries. Thus, the results of this study do not support the worry that marijuana dispensaries increase crime rates in the areas they are implemented or their surrounding areas.

Taking inspiration from the literature on alcohol outlets and using the crime pattern theory framework, hopefully additional insight has been gained through this project to make the comparison whether marijuana outlets act similarly to alcohol outlets as crime generators or attractors. With the insight from this study for policy-makers aside, this project provides additional understanding for those in research and academia. The geospatial analytical methods proposed in this thesis are not yet widely used within the criminological sphere, although there have been mentions and suggestions to their use. These methods are extensively used in the geographic sciences and some preliminary uses have been explored in some criminological studies, but there are additional methods and models that have not been adopted by criminologists yet. This study hopes that the exploration of these analytical methods can supplement existing methods to better understand and explain the spatial distributions of crime.

REFERENCES

Anderson, M. D., Hansen, B., & Rees, D. I. (2013). Medical marijuana laws, traffic fatalities, and alcohol consumption. *The Journal of Law and Economics*, 56(2), 333-369.

Andresen, M. A. (2010). The place of environmental criminology within criminological thought. In Classics in environmental criminology (pp. 21-44). CRC Press.

Anselin, L. (2001). Spatial econometrics. *A companion to theoretical econometrics*, Malden, MA: Blackwell Publishing Ltd, 310-330.

Anselin, L. & Bera, A. K. (1998). “Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics”. *Handbook of Applied Economic Statistics*, New York, New York: CRC Press, 237-289.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial analyses of crime. *Criminal Justice*, 4(2), 213-262.

Anselin, L., Le Gallo, J., & Jayet, H. (2008). Spatial panel econometrics. *The econometrics of panel data*, 625-660

Belotti, F, Hughes, G & Piano Mortari, A. (2017).Spatial panel data models using Stata. *The Stata Journal*, 17(1), 139-180.

Bernard, T. J., Snipes, J. B., & Gerould, A. L. (2015). Vold's Theoretical Criminology (7th ed.). New York: Oxford University Press.

Bernasco, W., & Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency*, *48*(1), 33-57.

Brantingham, P. J., & Brantingham, P. L. (Eds.). (1981). Environmental criminology. Beverly Hills, California: Sage Publication Inc.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3-28.

Brantingham, P. L., & Brantingham, P. J. (1993). Environment, routine and situation: Toward a pattern theory of crime. *Advances in criminological theory*, *5*(2), 259-94.

Brantingham, P., & Brantingham, P. (1995). Criminality of place. *European journal on criminal policy and research*, *3*(3), 5-26.

Brantingham, P. L., & Brantingham, P. J. (1998). Mapping crime for analytic purposes: location quotients, counts and rates. *Crime mapping and crime prevention*, *8*, 263-288.

Brinkman, J., & Mok-Lamme, D. (2017). Not in My Backyard? Not So Fast. The Effect of Marijuana Legalization on Neighborhood Crime.

California Police Chief's Association's Task Force on Marijuana Dispensaries. (2009) White Paper on Marijuana Dispensaries. Retrieved from http://www.chico.ca.us/document_library/departments/planning_department/mmj_87-156.pdf

Chang, T. Y., & Jacobson, M. (2017). Going to pot? The impact of dispensary closures on crime. *Journal of urban economics*, *100*, 120-136.

Cheon, H., Decker, S. H., & Katz, C. M. (2018). Medical Marijuana and Crime: Substance Use and Criminal Behaviors in a Sample of Arrestees. *Journal of Drug Issues*, 48(2), 182-204.

Clarke, R. V. (2009). The theory of crime prevention through environmental design. *Police Management Studies Quarterly*, 3(3), 344-356.

Clarke, R. V., & Felson, M. (1993). Routine activity and rational choice: Advances in criminological theory (Volume 5). Piscataway, NJ: Transaction.

Cohen, L. E., & Felson, M. (2016). Social Change and Crime Rate Trends: A Routine Activity Approach (1979). In Classics in Environmental Criminology (pp. 203-232). CRC Press.

Cole, J. M. (2013). Memorandum for All United States Attorneys: Guidance Regarding Marijuana Enforcement (United States, Department of Justice, Deputy Attorney General).

Contreras, C. (2017). A Block-Level Analysis of Medical Marijuana Dispensaries and Crime in the City of Los Angeles. *Justice Quarterly*, 34(6), 1069-1095.

Cozens, P., & Love, T. (2015). A Review and Current Status of Crime Prevention through Environmental Design (CPTED). *Journal of Planning Literature*, 30(4), 393–412. https://doi.org/10.1177/0885412215595440

DEA. (2018). Drug Scheduling. Retrieved December 15, 2018, from https://www.dea.gov/drug-scheduling

Dokoupil, T., & Briggs, B. (2014, February 20). Robbers target cash-based pot businesses. *CNBC.* Retrieved from https://www.cnbc.com/2014/02/05/robber-gangs-terrorize-colorado-pot-shops.html

Dugan, L. (2010). Estimating effects over time for single and multiple units. *Handbook of quantitative criminology*, Springer, New York, NY. (741-763).

Eck, J. E., & Weisburd, D. (1995). Crime and place, crime prevention studies. Monsey, NY: Criminal Justice Press. EckCrime and Place, Crime Prevention Studies4Monsey1995.

Elhorst, J. P. (2009). C. 2 Spatial Panel Data Models. Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications, 377.

ESRI. (2011). ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Dilley, J. A., Hitchcock, L., McGroder, N., Greto, L. A., & Richardson, S. M. (2017). Community-level policy responses to state marijuana legalization in Washington State. *International Journal of Drug Policy*, 42, 102-108.

Ferguson, B. (2014, January 16). Whether Statewide Initiative Establishing System for Licensing Marijuana Producers, Processors, and Retailers Preempts Local Ordinances. Washington State Office of the Attorney General. Retrieved from https://www.atg.wa.gov/ago-opinions/whether-statewide-initiative-establishing-system-licensing-marijuana-producers

Freisthler, B., Kepple, N. J., Sims, R., & Martin, S. E. (2013). Evaluating medical marijuana dispensary policies: Spatial methods for the study of environmentally-based interventions. *American Journal of Community Psychology*, *51*(1-2), 278-288.

Freisthler, B., Ponicki, W. R., Gaidus, A., & Gruenewald, P. J. (2016). A micro-temporal geospatial analysis of medical marijuana dispensaries and crime in Long Beach, California. *Addiction*, *111*(6), 1027-1035.

Freisthler, B., Gaidus, A., Tam, C., Ponicki, W. R., & Gruenewald, P. J. (2017). From medical to recreational marijuana sales: marijuana outlets and crime in an era of changing marijuana legislation. *The journal of primary prevention*, *38*(3), 249-263.

Frontline. (2018). Marijuana Timeline. Retrieved 2018, from https://www.pbs.org/wgbh/pages/frontline/shows/dope/etc/cron.html

General Social Surveys. (2018). NORC at the University of Chicago. Data accessed from the GSS Data Explorer website at gssdataexplorer.norc.org

Golgher, A. B., & Voss, P. R. (2016). How to interpret the coefficients of spatial models: Spillovers, direct and indirect effects. *Spatial Demography*, 4(3), 175-205.

Gorman, D. M., Gruenewald, P. J., & Waller, L. A. (2013). Linking places to problems: geospatial theories of neighborhoods, alcohol and crime. *GeoJournal*, *78*(3), 417-428.

Groff, E. R., & Lockwood, B. (2014). Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of Research in Crime and Delinquency*, *51*(3), 277-314.

Groff, E. R., Weisburd, D., & Yang, S. M. (2010). Is it important to examine crime trends at a local "micro" level?: A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology*, *26*(1), 7-32.

Gruenewald, P. J., Freisthler, B., Remer, L., LaScala, E. A., & Treno, A. (2006). Ecological models of alcohol outlets and violent assaults: crime potentials and geospatial analysis. *Addiction*, *101*(5), 666-677.

Han, B., Compton, W. M., Blanco, C., & Jones, C. M. (2018). Trends in and correlates of medical marijuana use among adults in the United States. Drug and alcohol dependence, 186, 120-129.

Hansen, B., Miller, K. S., & Weber, C. (2018). *Early Evidence on Recreational Marijuana Legalization and Traffic Fatalities* (No. w24417). National Bureau of Economic Research.

Hunt, P., Pacula, R. L., & Weinberger, G. (2018). High on Crime? Exploring the Effects of Marijuana Dispensary Laws on Crime in California Counties.

H.Amdt. 322 to H.R. 2578, 114th Cong. (2015) (enacted). https://www.congress.gov/amendment/114th-congress/house-amendment/332

H.R. 420, 116th Cong., (2019). https://www.congress.gov/bill/116th-congress/house-bill/420

Hunt, P. & Pacula, R.L. (2017). Early Impacts of Marijuana Legalization: An Evaluation of Prices in Colorado and Washington. *Journal of Primary Prevention*, (38)4, 221-248.

Jacobson, M., Chang, T., Anderson, J. M., MacDonald, J., Bluthenthal, R. N., & Ashwood, J. S. (2011). Regulating Medical Marijuana Dispensaries.

Kepple, N. J., & Freisthler, B. (2012). Exploring the ecological association between crime and medical marijuana dispensaries. *Journal of studies on alcohol and drugs*, *73*(4), 523-530.

Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built environment*, *34*(1), 62-74.

KOMO. (2014, November 18). 1 shot in rolling gun battle after Tacoma marijuana robbery. *Sinclair Broadcast Group.* Retrieved from https://komonews.com/news/local/1-shot-in-rolling-gun-battle-after-tacoma-marijuana-robbery-11-21-2015

Larue, E. M. (2013). Patterns of crime and universities: A spatial analysis of burglary, robbery, and motor vehicle theft patterns surrounding universities in Ottawa (Doctoral dissertation, Arts & Social Sciences: School of Criminology).

Maier, S. L., Mannes, S., & Koppenhofer, E. L. (2017). The implications of marijuana decriminalization and legalization on crime in the United States. *Contemporary Drug Problems*, *44*(2), 125-146.

Marijuana Policy Project. (n.d.). Medical Marijuana Dispensaries and Their Effect on Crime. *Marijuana Policy Project.* Retrieved from https://www.leg.state.nv.us/App/NELIS/REL/77th2013/ExhibitDocument/OpenExhibitDocument?exhibitId=8651&fileDownloadName=h0601sb374c_OKeK.pdf

Sarrias, M., (2017). Lecture 2: Spatial Models [PowerPoint slides]. Retrieved from Universidad Católica del Norte Spatial Econometrics Weebly site.

Sun, T., (2018). Lecture 10: Fixed-effect and Random Effects Models [PowerPoint slides]. Retrieved from University of Maryland Spatial Econometrics ELMS site.

Torres-Reyna, O., (2007). Panel Data Analysis: Fixed and Random Effects using Stata [PowerPoint slides]. Retrieved from Princeton University Princeton Library site.

Maxwell, J. C., & Mendelson, B. (2016). What Do We Know Now About the Impact of the Laws Related to Marijuana?. Journal of addiction medicine, 10(1), 3–12. doi:10.1097/ADM.0000000000000188

McCarty, K. (2018, April 25). Tacoma cannabis retailers frustrated by repeated break-ins. *Cox Media Group.* Retrieved from https://www.kiro7.com/news/local/tacoma-cannabis-retailers-frustrated-by-repeated-break-ins/737828420

McCord, Eric S., Jerry H. Ratcliffe, R. Marie Garcia, and Ralph B. Taylor. "Nonresidential crime attractors and generators elevate perceived neighborhood crime and incivilities." *Journal of Research in Crime and Delinquency* 44, no. 3 (2007): 295-320.

McDonald, P.R. & Pelisek, C. (2009, November 23). L.A.'s Medical Weed Wars. LA Weekly. Retrieved from https://www.laweekly.com/news/las-medical-weed-wars-2162644

Morris, R. G., TenEyck, M., Barnes, J. C., & Kovandzic, T. V. (2014). The effect of medical marijuana laws on crime: evidence from state panel data, 1990-2006. *PloS one*, *9*(3), e92816.

Morrison, C., Gruenewald, P. J., Freisthler, B., Ponicki, W. R., & Remer, L. G. (2014). The economic geography of medical cannabis dispensaries in California. *International Journal of Drug Policy*, 25(3), 508-515.

Municipal Research and Services Center. (2018, December 14). Marijuana Regulation in Washington State. Retrieved from http://mrsc.org/Home/Explore-Topics/Legal/Regulation/Marijuana-Regulation-in-Washington-State.aspx

National Alliance for Model State Drug Laws. (2016, December 23). Marijuana: Comparison of State Laws Legalizing Person, Non-Medical Use. Retrieved from http://www.namsdl.org/library/33FD7B09-D862-91A9-48FFEFD87F5D4611/

National Conference of State Legislatures. (2018, November 8). State Medical Marijuana Laws. Retrieved from http://www.ncsl.org/research/health/state-medical-marijuana-laws.aspx

Pacula, R. L., & Smart, R. (2017). Medical marijuana and marijuana legalization. *Annual review of clinical psychology*, 13, 397-419.

Parker, R. N. (2004). Alcohol and violence: connections, evidence and possibilities for prevention. *Journal of Psychoactive Drugs*, *36*(sup2), 157-163.

Parker, R. N., & Auerhahn, K. (1998). Alcohol, drugs, and violence. *Annual review of sociology*, *24*(1), 291-311.

Pew Research Center. (2010, April 1). Public Support for Legalizing Medical Marijuana: Modest Rise in Percentage Favoring General Legalization. Retrieved from http://www.pewresearch.org/wp-content/uploads/sites/4/legacy-pdf/4-4-13-Marijuana-Release.pdf

Pew Research Center. (2013, April 3). Majority Now Supports Legalizing Marijuana . Retrieved from http://www.people-press.org/files/legacy-pdf/602.pdf

Pew Research Center. (2014, June 26). Beyond Red vs. Blue: The political typology. Retrieved from http://www.pewresearch.org/wp-content/uploads/sites/4/2014/06/6-26-14-Political-Typology-release1.pdf

Ratcliffe, J. H. (2006). A temporal constraint theory to explain opportunity-based spatial offending patterns. *Journal of Research in Crime and Delinquency*, 43(3), 261-291.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American journal of sociology*, 94(4), 774-802.

Sarvet, A. L., Wall, M. M., Fink, D. S., Greene, E., Le, A., Boustead, A. E., … Hasin, D. S. (2018). Medical marijuana laws and adolescent marijuana use in the United States: a systematic review and meta-analysis. Addiction (Abingdon, England), 113(6), 1003–1016. doi:10.1111/add.14136

Schneider, R. H. (2005). Introduction: Crime prevention through environmental design (CPTED): Themes, theories, practice, and conflict. *Journal of architectural and planning research*, 271-283.

Scribner, R. A., MacKinnon, D. P., & Dwyer, J. H. (1995). The risk of assaultive violence and alcohol availability in Los Angeles County. *American Journal of Public Health*, *85*(3), 335–340.

Scribner, R., Cohen, D., Kaplan, S., & Allen, S. H. (1999). Alcohol availability and homicide in New Orleans: conceptual considerations for small area analysis of the effect of alcohol outlet density. *Journal of studies on alcohol*, *60*(3), 310-316.

Shaw, C. R., & McKay, H. D. (1942). Juvenile delinquency and urban areas. Chicago, IL, US: University of Chicago Press.

Shi, Y., Meseck, K., & Jankowska, M. M. (2016). Availability of medical and recreational marijuana stores and neighborhood characteristics in Colorado. *Journal of addiction*, 2016.

Slocum, Lee Ann, Andres F. Rengifo, Tiffany Choi, and Christopher R. Herrmann. "The elusive relationship between community organizations and crime: an assessment across disadvantaged areas of the South Bronx." *Criminology* 51, no. 1 (2013): 167-216.

Smart, R., Caulkins, J. P., Kilmer, B., Davenport, S., & Midgette, G. (2017). Variation in cannabis potency and prices in a newly legal market: evidence from 30 million cannabis sales in Washington state. *Addiction*, 112(12), 2167-2177.

Steenbeek, Wouter, Beate Volker, Henk Flap, and Frank van Oort. "Local businesses as attractors or preventers of neighborhood disorder." *Journal of Research in Crime and Delinquency* (2011): 0022427810397948.

Subica, A. M., Douglas, J. A., Kepple, N. J., Villanueva, S., & Grills, C. T. (2018). The geography of crime and violence surrounding tobacco shops, medical marijuana dispensaries, and off-sale alcohol outlets in a large, urban low-income community of color. *Preventive medicine, 108*, 8-16.

Sun, D. (2018, April 06). After a string of robberies, pot shops call for state's help. *Cox Media Group.* Retrieved from https://www.kiro7.com/news/local/after-a-string-of-robberies-pot-shops-call-for-states-help/727885863

Tacoma, WA. (n.d.). Retrieved January 22, 2019, from https://datausa.io/profile/geo/tacoma-wa/

Tacoma, Washington. (n.d.). Retrieved January 22, 2019, from https://www.citytowninfo.com/places/washington/tacoma

Tacoma, Washington, Title 13 – Land Use Regulatory Code, (2018)

Tacoma, Washington, Substitute Ordinance No. 28343. (2016)

Tacoma, Washington, Substitute Ordinance No. 28462. (2017)

Tacoma, Washington, Substitute Ordinance No. 28361. (2016)

Thomas, C., & Freisthler, B. (2016). Examining the locations of medical marijuana dispensaries in L os A ngeles. *Drug and alcohol review*, 35(3), 334-337.

United States Census Bureau. (2018). Welcome to Geocoder. Retrieved from https://geocoding.geo.census.gov/

Vigil, D. I., Van Dyke, M., Hall, K. E., Contreras, A. E., Ghosh, T. S., & Wolk, L. (2018). Marijuana Use and Related Health Care Encounters in Colorado Before and After Retail Legalization. International Journal of Mental Health and Addiction, 1-7.

Viton, P. A. (2010). Notes on spatial econometric models. City and regional planning, 870(3), 2-17.

Wang, H. M., & Herrera, V. H. (2014, March). A note of marijuana legalization and arrest rates in the United States. In *A Paper Presented at the Academic and Business Research Institute Conference. San Antonio, TX*.

Washington State Senate (n.d.). History of Washington State Marijuana Laws. Retrieved from http://www.ncsl.org/documents/summit/summit2015/onlineresources/wa_mj_law_history.pdf

Wasserman, M. (2018, February 03). Rob a pot shop, serve more time. A bill in the state Legislature could make it happen. *The News Tribune.* Retrieved from https://www.thenewstribune.com/news/politics-government/article197443149.html

Wortley, R., & Mazerolle, L. (2008). Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In R. Wortley & L. Mazerolle (eds). *Environmental criminology and crime analysis*, 1-18. Cullompton, UK: Willan.

Winston, J. (2016, June 27). Are Weed Dispensary Robberies On The Rise? *Merry Jane.* Retrieved from https://merryjane.com/news/are-weed-dispensary-robberies-on-the-rise

Wortley, R., & Townsley, M. (2016). Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In R. Wortley & M. Townsley, M. (eds). Environmental Criminology and Crime Analysis (2nd ed). London: Routledge. ISBN 9781138891135

Zheng, Y. (2014). Medical Marijuana Dispensaries Ban: Bill Sent to House Committee, Faces Uncertain Fate. The Oregonian . March 4, 2014.